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Land, Water, Infrastructure And People: Considerations Of Planning For Distributed Stormwater Management Systems

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Abstract

When urbanization occurs, the removal of vegetation, compaction of soil and construction of impervious surfaces—roofs, asphalt, and concrete—and drainage infrastructure result in drastic changes to the natural hydrological cycle. Stormwater runoff occurs when rain does not infiltrate into soil. Instead it ponds at the surface and forms shallow channels of overland flow. The result is increased peak flows and pollutant loads, eroded streambanks, and decreased biodiversity in aquatic habitat. In urban areas, runoff is typically directed into catch basins and underground pipe systems to prevent flooding, however such systems are also failing to meet modern environmental goals. Green infrastructure is the widely evocative idea that development practices and stormwater management infrastructure can do better to mimic the natural hydrological conditions through distributed vegetation and source control measures that prevent runoff from being produced in the first place. This dissertation uses statistics and high-resolution, coupled surface-subsurface hydrologic simulation (ParFlow.CLM) to examine three understudied aspects of green infrastructure planning. First, I examine how development characteristics affect the runoff response in urban catchments. I find that instead of focusing on site imperviousness, planners should aim to preserve the ecosystem functions of infiltration and evapotranspiration that are lost even with low density development. Second, I look at how the spatial configuration of green infrastructure at the neighborhood scale affects runoff generation. While spatial configuration of green infrastructure does result in statistically significant differences in performance, such differences are not likely to be detectable above noise levels present in empirical monitoring data. In this study, there was no evidence of reduced hydrological effectiveness for green infrastructure located at sag points in the topography. Lastly, using six years of empirical data from a voluntary residential green infrastructure program, I show how the spread of green infrastructure depends on the demographic and physical characteristics of neighborhoods as well as spatially-dependent social processes (such as the spread of information). This dissertation advances the science of green infrastructure planning at multiple scales and in multiple sectors to improve the practice of urban water resource management and sustainable development.

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LAND, WATER, INFRASTRUCTURE AND PEOPLE: CONSIDERATIONS OF PLANNING FOR DISTRIBUTED STORMWATER MANAGEMENT SYSTEMS

To my family.

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ABSTRACT

LAND, WATER, INFRASTRUCTURE AND PEOPLE: CONSIDERATIONS OF PLANNING FOR DISTRIBUTED STORMWATER MANAGEMENT SYSTEMS

Theodore Chao Lim

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When urbanization occurs, the removal of vegetation, compaction of soil and construction of impervious surfaces—roofs, asphalt, and concrete—and drainage infrastructure result in drastic changes to the natural hydrological cycle. Stormwater runoff occurs when rain does not infiltrate into soil. Instead it ponds at the surface and forms shallow channels of overland flow. The result is increased peak flows and pollutant loads, eroded streambanks, and decreased biodiversity in aquatic habitat. In urban areas, runoff is typically directed into catch basins and underground pipe systems to prevent flooding, however such systems are also failing to meet modern environmental goals. Green infrastructure is the widely evocative idea that development practices and stormwater management infrastructure can do better to mimic the natural hydrological conditions through distributed vegetation and source control measures that prevent runoff from being produced in the first place. This dissertation uses statistics and high-resolution, coupled surface-subsurface hydrologic simulation (ParFlow.CLM) to examine three understudied aspects of green infrastructure planning. First, I examine how development characteristics affect the runoff response in urban catchments. I find that instead of focusing on site imperviousness, planners should aim to preserve the ecosystem functions of infiltration and evapotranspiration that are lost even with low density development. Second, I look at how the spatial configuration of green infrastructure at the neighborhood scale affects runoff generation. While spatial configuration of green infrastructure does result in

statistically significant differences in performance, such differences are not likely to be detectable above noise levels present in empirical monitoring data. In this study, there was no evidence of reduced hydrological effectiveness for green infrastructure located at sag points in the topography. Lastly, using six years of empirical data from a voluntary residential green infrastructure program, I show how the spread of green infrastructure depends on the demographic and physical characteristics of neighborhoods as well as spatially-dependent social processes (such as the spread of information). This dissertation advances the science of green infrastructure planning at multiple scales and in multiple sectors to improve the practice of urban water resource management and sustainable development.

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URBANIZATION AND THE PROBLEM OF STORMWATER RUNOFF

Stormwater runoff occurs when rain does not infiltrate into soil. Instead it ponds at the surface and forms shallow channels of overland flow. Stormwater runoff is the most visible response of land to rain. In urban areas, runoff is typically directed into catch basins and underground pipe systems to prevent the flooding of property and infrastructure. When it rains, the majority of us do not stop to think of where that water goes. As long as it does not flood, most urban residents do not care about how the infrastructure is functioning. However, in cities in the United States, drainage infrastructure in many of our oldest and densest cities are in great need of upgrade. The problem of stormwater runoff affects urban areas in two ways: through the regulatory goals and standards for infrastructure in the Clean Water Act, and through the expectations of long-term resilience and sustainability of our communities. To begin this dissertation, I draw on two examples of how stormwater runoff effects cities to illustrate these two problems: the case of Philadelphia's Combined Sewer Overflow Long Term Control Plan *Green City Clean Waters*, and the case of the 2016 flooding of the historic downtown of Ellicott City, Maryland. These two examples illustrate means through which planning practice can improve urban stormwater management issues: through capital improvements programs for infrastructure investment and through zoning and subdivision regulations for land management.

Philadelphia's infrastructure for draining stormwater away from development is referred to as a "combined sewer system" (CSS). This means that stormwater runoff and domestic wastewater are collected within the same pipe network. During dry weather and small rainfall events, the wastewater/stormwater runoff mix is conveyed to one of three wastewater treatment plants (WWTPs) operated by the city. However, during many larger rain events, the volume of stormwater runoff overwhelms the capacity of the conveyance, storage and treatment infrastructure, and the excess volume overflows, untreated, from outfalls of the pipe system into natural streams and rivers. This discharge of raw sewage is called a “combined sewer overflow” (CSO). Before the most recent efforts to mitigate CSO events, an average of 8 billion gallons of untreated sewage/stormwater overflowed from the system each year (Philadelphia Water Department, 2011), a violation of the Clean Water Act (CWA).

Figure 1.1 Litter discharged from a combined sewer overflow (outlet not shown, but located at the lower right of the photograph) spreads through Tacony Creek in North Philadelphia. Photo by the author

Philadelphia's approach to this problem is to use "source control" methods to intercept surface runoff close to where it forms to prevent it or from ever entering the collection system. Such source control methods include building rain gardens, tree trenches, and permeable pavement that encourage runoff to infiltrate into soils and evapotranspire back into the atmosphere. These source control methods are also known as "green infrastructure" (GI), low impact development (LID), or stormwater best management practices (BMPs). By 2036, the city's agreement with the US Environmental Protection Agency requires that the 1" rainfall event for nearly 10,000 acres of impervious surfaces (such as roofs, concrete and asphalt) within the city be treated with GI. This area amounts to one-third of the total CSS area of the city and is the most ambitious GI plan adopted in the country to bring local stormwater/sewer infrastructure into compliance with the CWA. The costs needed to upgrade aging water infrastructure to meet modern environmental standards in the US are estimated to be over $60 billion and are mostly a local expenditure. According to the US Conference of Mayors, water infrastructure spending is the second highest local expenditure after education. Delayed maintenance of drainage infrastructure has resulted in local water and sewer rates in many cities that are rising three times faster than inflation (US Conference of Mayors, 2007). Therefore, the management of and planning for stormwater runoff and infrastructure is a pervasive local issue with national-scale implications that very few residents are actually aware of. Philadelphia's plan to use GI to upgrade its infrastructure, called *Green City, Clean Waters*, is based on the premise that cost savings can be reached by incorporating the multiple benefits of GI (environmental amenity, community health, etc), but presents the challenge of how the land surface area to construct such large amounts of GI will be obtained within an already built-out city, with slow redevelopment rates (Philadelphia Water Department, 2009).

My second example illustrates how new development can also make existing development more flood prone. On July 30, 2016, the historic downtown of Ellicott City, MD was destroyed by a flood that also claimed the lives of two people. The Howard County Council responded by considering enacting a nine-month development moratorium to examine how development increases flood risk (Waseem, 2016). In the end however, development pressure in the county resulted in the tabling of the proposed moratorium. The benefits that society receives from undeveloped lands, such as forests, are called "ecosystem services." Not typically counted as formal assets of cities, they nonetheless provide critical functions to society, such as flood mitigation, that are overlooked in favor of the economic incentives of land development. Only after disasters such as that of the 2016 flooding of downtown Ellicott City, are alternatives to development considered. Even then, the economic pressures of development will continue to win out if the benefits of natural lands remain under-recognized. This ambivalence exemplifies a central tension in regional urban and environmental planning: that planners are pressured to function as part of the urban growth machine, yet must simultaneously ensure environmental quality alongside development.

The above two examples illustrate why it is necessary to adopt the best planning practices for integrated land, water, and infrastructure interventions. These practices need to be able to both protect natural water bodies and to recognize the ecosystem services existing communities derive from natural lands, and to do so at multiple scales. This is especially true as problems associated with urban stormwater management are only expected to become more severe with population growth and climate change (USGCRP, 2009; Kunkel *et al.*, 2012; AECOM, 2013).

In this dissertation, I explore the hydrological function GI has at various scales and how distributed GI implementation has actually occurred.

There are three central propositions:

1. Land conservation results in better hydrological outcomes than engineered GI that treats runoff from urban development.
2. Clustered spatial configurations of GI networks in urban areas may result in lower-than-expected ability to mitigate overland flows due to lateral interactions between facilities a delayed capacity recovery between storm events.
3. The dynamics of voluntary residential adoption of distributed engineered GI networks have the potential to result in clusters of adoption within cities, due both to clusters of land suitability and social preferences within cities, and due to social processes of new technology adoption.

Exploration of these propositions will increase planners' understanding of GI function and implementation processes. This will increase their ability to weigh land conservation against new development, decide how to invest time and resources into outreach to residents to encourage GI construction on private property, and plan for changing participation rates in voluntary programs to better adapt communities to changing urbanization and climate conditions.

CHAPTER OVERVIEW

In this dissertation I bridge key issues of the urban runoff, land management, and infrastructure and explore implications for urban environmental planning. In **Chapter 2** I give more detail about the regulatory context of stormwater management and the intellectual roots of GI. In this chapter, I show how the current focus on untreated stormwater discharges from Combined Sewer Systems (CSS) took decades after the enactment of the Clean Water Act to become defined and regulated as “point sources” of pollution. Doing so assigned accountability for eliminating combined sewer over flow (CSO) events, but successfully attaining this goal requires recognition of socio-ecological systems challenges of large-area generated point sources. Adaptive management and urban experimentation are current management paradigms that frequently assess outcomes and correct course if intermediate goals are not met. This type of environmental policy is frequently used for socio-ecological systems where there are frequently nonlinearities, high levels of uncertainty and complex interconnections between biophysical and social system elements, which is the case for runoff management and urban development, land management and infrastructure systems.

In **Chapter 3** I contextualize the changes in hydrological function associated with different types and intensities of development at the regional scale, addressing **Proposition 1**, above. In this chapter, I examine the effect of the proportion of land that is covered by impervious area. Impervious area has been the major causal focus of degraded hydrological function associated with urbanization. I develop a statistical methodology to detect evidence of reduced watershed capacitance to classify over 100 urbanized watersheds from continuous stream flow data, then regress this classification on the characteristics of the urbanized watersheds. The results of this chapter show that reduced storage is determined more by development, than type of development, and that low-density suburban development and urban green space functions more similarly to highly impervious areas than to naturalized land. This finding highlights the importance of accounting for environmental changes accompanying urbanization beyond imperviousness, including: changes to hydraulic conductivity and reduced evapotranspiration rates because of vegetation change, highlighting the importance of land conservation over type of development in preserving hydrologic function.

In **Chapter 4** I describe the application of a three-dimensional surface-subsurface hydrological simulation model, ParFlow.CLM to an urbanized sewershed (approximately three urban blocks), to test **Proposition 2**, above. This application is unique for two reasons. First, the majority of urban hydrological models focus on site imperviousness in order to predict runoff flows and volumes that load conventional infrastructure—piped drainage systems—assuming that water that is infiltrated into soils has “exited” the system. If GI is extensively implemented within a catchment however, it is important to account for subsurface dynamics after infiltration into soils and evapotranspiration on the site. ParFlow.CLM accounts for these processes in three dimensions, allowing me to identify important network interactions in hydrological function at the catchment scale. Secondly, the study site that is modeled, located in Washington DC, collected in-pipe flows before and after the installation of GI in the public right-of-way (ROW) and on private properties, between 2009 and 2015. This data allowed for comparisons of the applied ParFlow.CLM model to this site with empirical data.

In **Chapter 5** I use the ParFlow.CLM model developed for the site in Chapter 4 to test nine alternative spatial configuration scenarios for the GI network and building footprints within the sewershed, testing **Proposition 2**, above. The nine scenarios reflect policy and planning-relevant interventions related to site management and development and are thus directly related to adaptive management actions that a city could choose to enact. Differences in the event-based runoff responses are detected between scenarios, with GI configurations located in high flow accumulation areas intercepting more runoff. However, compared to the amount of variation in the observed monitoring data, only the differences in performance between the most optimal spatial configuration and the least optimal spatial configuration would likely be detectable through monitored pipe flows.

In **Chapter 6** I analyze six years of citywide, voluntary residential GI program participation data to determine the physical and socio-economic determinants of program participation in Washington DC, testing **Proposition 3**, above. While other studies have emphasized physical feasibility of GI construction on private properties and financial incentives for property owners, this study characterizes the growth of the program over time and space. Controlling for the tendency for similar types of individuals to spatially cluster within the city, this analysis shows that the effect of spatially-dependent social processes becomes more important as the program matures. The results of the statistical analysis are supported by findings from a survey of participants that indicates that a major determinant of program participation is hearing about the program from a friend or neighbor. This indicates that GI adoption, like other environmental behaviors, can be thought of as a social process of new technology adoption, dependent on social capital and information networks, in addition to a function of personal preferences or property characteristics. For urban planners, this demonstrates an approximate timescale of voluntary, bottom-up programs that may be used alongside more top-down zoning, subdivision regulations, and capital improvements programs to manage stormwater in cities.

Lastly, in **Chapter 7** I summarize the conclusions of the dissertation and offer policy recommendations for cities and regions to achieve more sustainable outcomes through water resource management and planning.

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CHAPTER 2: INTELLECTUAL ROOTS AND REGULATORY CONTEXT OF GREEN INFRASTRUCTURE

INTRODUCTION

Green infrastructure is a concept that recognizes the interrelationships between land, water, and drainage infrastructure. Green Infrastructure (GI) can have different meanings in different contexts and at different scales. Embracing the ability of the term to be evocative in many different fields, I broadly define GI as an integrated, ecological approach to land, water and built infrastructure management that meets multiple objectives of sustainability: environmental, financial and community benefits. Integrated land and water management approaches can span many scales: from conservation planning at the regional scale, to a homeowner's decision to adopt a rain garden to manage the stormwater runoff from their own roof.

Understanding the science of GI is essential for practice. In the following chapters of this dissertation, I address impacts of regional development on streamflow patterns, the implications of spatial configuration of imperviousness and GI networks within cities, and the spatial-temporal social process of voluntary adoption of GI by urban residents. In this chapter, I address the intellectual and regulatory roots of GI to situate the importance of my research within larger conversations in environmental policy, planning, and socio-ecological systems.

HISTORICAL ROOTS OF GREEN INFRASTRUCTURE

The concept of GI has intellectual roots originating in two related areas: ecosystem services and urban sustainability. Although the ideas of ecosystem services and urban sustainability are not mutually exclusive, they approach GI from two different directions.

The Ecosystem Services Origins of Green Infrastructure

Ecosystem services, a term popularized in the 2005 United Nations Millennium Ecosystems Assessment initiative, is a recognition of the critical processes that human society derives from nature (Millennium Ecosystem Assessment, 2005). Undeveloped, natural areas provide ecosystem services including food production, timber, recreation, water filtration and storage, and heat island mitigation through forests, agricultural lands, and open space. Calling such regional-scale lands "green infrastructure" recognizes the importance of these ecosystem services to society and underscores the need to value and actively plan for the conservation of natural areas and working lands alongside development, just like other critical infrastructures, such as sewer and water facilities. Further, planning for the conservation of these areas cannot be piecemeal; rather, using the ecological concept of patches, all types and sizes of GI should be thought of part of an integrated network (Benedict and McMahon, 2006). In this view of GI, the goal is to preserve ecological function as our planet becomes increasingly urbanized. And maintaining the connectivity of green infrastructure is considered key to maximizing ecosystem services (ibid.). The central questions are of the ecological impact of development and the quantification of costs and benefits of urbanization inclusive of ecological impacts and ecosystem services. The term 'infrastructure' suggests that society think of these ecosystem services as infrastructural – complete with standards and protocols that make transparent its embeddedness in society (Star, 1999). Infrastructure also implies that there should be long-term financing for construction and annual operations and maintenance costs for these systems.

Though the term "ecosystem services" can be traced to within the past 15-20 years, the idea that planning for development should incorporate consideration of the natural environment can be traced back much further. Early regional planners in the first half of the 20th century stressed the importance of natural land conservation. Increasing urbanization in the late 19th century led the birth of the field of urban planning. Such regional planning thinkers as Patrick Geddes, Benton MacKaye and Lewis Mumford, recognized the need to balance the processes of urbanization with regional environmental quality (Mackaye, 1940; Geddes, 1949; Mumford, 1961). Initiatives to limit and contain urban development, such as greenbelts and urban growth boundaries, which are growth management tools still commonly used today, can be traced back to the work of these early regional planners. Later, Ian McHarg, who joined the fields of landscape architecture and environmental planning, wrote his seminal work *Design with Nature*, using overlays of environmental data to help guide development away from areas with high ecological value (McHarg, 1969). In the 1990s, contemporary site design initiatives such as Charles Little's Greenways for America, and New Urbanism and Smart Growth also valued compact development morphologies that acknowledged and promoted conservation of ecosystem services alongside development (Little, 1990; Duany and Plater-Zyberk, 1991; Daniels, 2001). Rather than characterize naturalized areas as the absence of development, environmental planners recognized that urban areas could not be sustained without the supporting functions of natural lands. A clear example of an urban area's formal recognition of the ecosystem service of water supply and purification derived from outside its political borders is New York City's purchase of thousands acres of land and conservation easements upstate to preserve the source of the city's drinking water supply. The investment in preservation of the land in 1997 was estimated at $1.5 billion, while the cost to construct treatment facilities large enough to treat the city's water demand would have cost $6 billion at the time, and $250 million annual to operate (NYC DEP, 2017). Today, New York City is known for its high quality potable water, due to the ecosystem services of filtration, purification, and storage that the forested and mountainous land provides to the city.

The Urban Sustainability Origins of Green Infrastructure

A second, distinct conceptualization of GI—that of urban sustainability—focuses on the functions and metabolisms of the city. In 1997, Rees asked the question, “Is ‘Sustainable City’ an Oxymoron?,” spurring a line of scholarship that examines how cities can improve environmental performance, often in contrast to other types of urbanized development, such as suburbs (Rees, 1997; Portney, 2003; Owen, 2009). This line of scholarship focuses on the dissection of urban processes and how cities can adopt plans and policies to achieve the triple bottom line goals of sustainability: environmental, economic, and social health (Campbell, 1996). Emergence of environmental design standards, such as the US Green Building Council’s Leadership in Energy and Environmental Design (LEED) and the US Department of Energy’s EnergyStar rating systems codified environmental performance and ‘green-ness’ *into* development. From this perspective of GI, the emphasis is not on recognizing the previously ignored ‘infrastructural’ ecosystem services that society derives from nature, but on imposing ‘green’ objectives for conventional urban infrastructures. Infrastructure is itself is an ecological concept. It facilitates not only material and energy flows between cities and their hinterlands, but also organizes the actors, institutions and regulations that govern and are affected by those material and energy flows. Therefore, greening a city and its infrastructure could include a palette of improvements to the urban landscape such as Low Impact Development (LID), solar panel programs, and clean energy bus fleets. Making cities more sustainable is also frequently equated with making them more desirable places to live, and cities see sustainability as part of developing a ‘competitive advantage’ over other cities to attract and keep populations (Portney, 2009).

The concept of infrastructure planning to meet multiple rather than singular goals has been a transformative force in infrastructure planning, operations and management, institutions, politics and processes (Brown, 2005; Farrelly and Brown, 2011; Karvonen, 2011). The greening discourse’s simultaneous emergence with sustainability has additional associations with ‘green-ness’ to environmental performance, including personal and community health and economic efficiency. In some circumstances it is actually these aspects of green-ness—not the specifics of environmental performance—that the public actually desires and understands. For example, the previous Water Commissioner of Philadelphia, Howard Neukrug, who played a major role in beginning one of the most aggressive green stormwater infrastructure programs in the country, recently stated in an interview that the decision to implement GI represented a shift away the conventional engineering conceptualization of ‘sustainable’ infrastructure as the most durable solution that resists aging and decay, towards a conceptualization of infrastructure that helps a community meet multiple goals of growth, revitalization and broader ecological benefits (Mittermaier, 2016). With respect to stormwater, GI redefines stormwater runoff as a resource to improve urban environmental function and amenity, rather than a waste to be disposed of (Bos and Brown, 2012; Hamel *et al.*, 2013).

Interdisciplinary Thinking and Green Infrastructure Concepts

Although one might be tempted to differentiate ‘types’ of GI according to rural and urban locations, this would ignore important intersections between the desire to improve urban environmental performance and acknowledgement of critical benefits humans derive from nature. Cities seek to draw the benefits of ecosystem services into their borders in order to improve livability for their residents. For example, since the days of rapid urban growth during industrialization, Frederick Law Olmsted, father of the field of landscape architecture and designer of New York City's Central Park and Boston's Emerald Necklace, advocated for areas of naturalized aesthetic within cities where residents could find physical and mental respite from the stresses of the city, but that were also engineered to provide naturalized stormwater management and flood regulating functions (Eisenman, 2013).

Within the field of landscape architecture, the rejection of the dichotomous presentation of nature and the urban as oppositional has become clearer. This is especially true most recently within the landscape urbanism movement, and some have suggested that the idea of *landscape,* rather than previous emphasis on buildings and engineered infrastructure components of the urban environment, is the most inclusive concept to capture the confluence, integration, and fluid exchange between environmental and engineered infrastructure systems (Waldheim, 2006). In recognition of the creation of more environmental problems resulting from large-scale, centralized urban infrastructures, this movement purports a vision of "urbanism beyond engineering," in which design, with its unifying ecological theories, can take a more central role in guiding sustainable development (Bélanger, 2009).

Common historical ties between the fields of landscape architecture, urban planning and civil engineering from over 100 years ago have made GI an attractive and evocative concept across these fields. The benefits to urban areas and the recognition of the effects of urbanization on environmental conditions have made many enthusiastic about incorporating GI into the future of infrastructure management. The shortcomings of the large, centralized, technocratic planning and engineering design practices of the previous century of infrastructure development are necessarily our current starting point. Today we deal with the physical, institutional and regulatory legacies of infrastructures planned in another century.

THE REGULATORY CONTEXT OF STORMWATER MANAGEMENT AND GREEN INFRASTRUCTURE

Legacy Stormwater Infrastructure Systems

During the 19th and 20th centuries, the "Sanitary City" model of urban development was dominant (Melosi, 2000). Under this model, the current scientific and engineering understanding and values of efficiency of development led to infrastructure designs where wastewater and stormwater runoff were conveniently channeled into nearby creeks that would flush out and dilute wastes into rivers, lakes and bays. In Philadelphia, over 20 streams that originally meandered across the city were buried and sewered so that a rational, efficient street grid system could be built (Levine, 2012). Roughly one third of the land area of Philadelphia is served by a Combined Sewer System, which collects sewage and stormwater runoff within the same pipes. This main branches of this system are also collocated where previous streambeds flowed, since these are areas in the topography where water tends to accumulate. The efficiency of the design to quickly channel away wastewater and drain the city made it the cutting-edge technology of its day (Tarr and Dupuy, 1988).

Today there are still 688 communities served by CSSs in the US. During dry weather, these systems convey wastewater to treatment plants, but during rain storms, they function as they did over 100 years ago: discharging a mixture of raw sewage and stormwater runoff into a receiving water body when the sewage volume flowing to a wastewater treatment plant exceeds the plant's capacity (**Figure 2.1)**. Although such systems allowed wastes and water to be drained away from properties, decreasing incidents of urban diseases of the day, today, our higher environmental standards and better understanding of ecology and the hydrological cycle have made these original CSS infrastructure functions unacceptable.

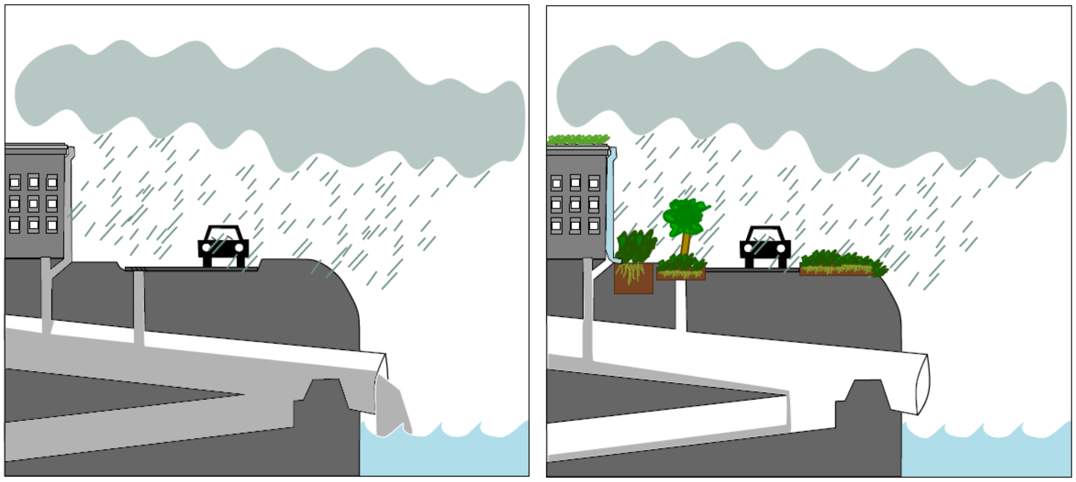

Figure 2.1 (Left) The typical function of a CSS (Combined Sewer System). During rain events, the capacity of the conveyance system is overwhelmed and overflows a mixture of untreated wastewater and stormwater runoff into surrounding water bodies. (Right) The intended function of GI is to intercept runoff near where it falls, before it enters the CSS. This prevents the system from being overwhelmed and from raw sewage discharges into natural water bodies.

However, separating wastewater and stormwater collection systems to meet current environmental standards is physically and economically infeasible for most CSS-served communities. GI helps fill this gap in infrastructure function by intercepting rainfall close to where it falls, and using the natural processes of infiltration and evapotranspiration to prevent or slow it from even entering the conventional infrastructure systems (**Figure 2.1**). From the perspective of the environmental regulation and management of our existing infrastructure systems, GI decreases the loadings onto the infrastructure and can be used to decrease Combined Sewer Overflow (CSO) events – when raw sewage is discharged into the environment. It is also used to filter contaminants and slow flows through Municipal Separate Sewer Systems (MS4s) that collect stormwater separately from domestic sewage, but directly discharge it into surrounding water bodies.

Developing notions of connections between land, water and infrastructure

As those of the landscape urbanism movement have recognized, and what more engineers and urban planners are also beginning to realize, is that our understanding of urban hydrology now indicates that restoration and preservation of quality aquatic habitat is not only about permissible infrastructure function according to current regulations. It is about bridging previously severed conceptual links between 'the urban' and 'nature.' This necessarily touches on issues of the relationship of humans to the environment, the relationships of humans to one another and institutions, and better understanding of the physical processes linking the built and natural environments, all of which can be examined at multiple scales. This necessitates a broader view of relevant system components.

Compared to 1900, we live in a much more urbanized society. In 2009 a majority of the world's population lived in urban areas for the first time in history (United Nations, 2014). The type of urban development has also changed (Angel *et al.*, 2011). In part a response to the poor environmental conditions and crowding of Industrial-era cities, in part a function of automobile-centric development and the interstate highway system, the process of urbanization in the United States has resulted in sprawling suburban development (Jackson, 1985). This type of urbanization converts farm fields and forest land to low density development, which while it may have lower overall levels of impervious surface than urban cores, nevertheless has been shown to have large impacts on the hydrological cycle (Booth and Jackson, 1997; Hekl and Dymond, 2016). Such widespread land cover and vegetation change does not only impact aquatic habitat quality. It can also impact existing downstream development, whose drainage infrastructure can become easily overloaded with runoff resulting from development that occurs after the sizing of its infrastructure, as illustrated by the example of flooding of the historical downtown of Ellicott City, MD mentioned in Chapter 1.

Green Infrastructure and the Clean Water Act

The intellectual development of the concept of GI and the relationships between land management and water resource quality was also reflected in federal environmental regulation. Surface water quality in the United States is primarily regulated by the Clean Water Act (CWA). The evolution of the focus of the CWA regulation reflects an increasing recognition of distributed, large-area generated sources of water pollution and the need to treat water resource management as an integrated socio-ecological system that includes land, legacy infrastructure, and social system dynamics. This evolution has occurred over four decades and is important to understanding the barriers to integrated, systematic GI implementation that still exist today.

In this section I show how the CWA-based regulation has been successful in reducing discrete sources of pollution that have clearly assignable accountability. Today we see can see the application of such regulatory strategies to infrastructure system regulation to eliminate combined sewer overflows and improve the function of separated sewer systems. However, unlike past environmental regulation, mere assignment of accountability and property rights-based pollution control techniques are unlikely to be successful for sources of pollution generated from large areas. Instead, a systems-perspective of negotiation, collaboration and broader cultural change is necessary. The lack of systems-perspective prevents proper contextualization of the function of GI at the different scales presented in the above section. Specifically, the current CWA regulatory focus overemphasizes GI as the “greening of infrastructure” and underemphasizes the “infrastructuring of green-ness” intellectual roots of GI presented above. This has also resulted in insufficient policy and scientific connections between the two, preventing scaling up of the benefits associated with GI.

The set of policies that we normally refer to as “The Clean Water Act” (CWA) are the set of 1972 amendments to the Federal Water Pollution Control Act, passed in 1948, and their subsequent amendments. In 1972, Congress gave administrative authority to the then-newly created Environmental Protection Agency to draft, implement and enforce the vision of the Act. From its onset, the CWA included two complimentary approaches.

Discharge Permit Regulations

The first is a technology-based approach, which considers the selection of best available practices and technologies for reducing discharge of harmful contaminants into the aquatic environment unique to specific industries. Dependent on the technologies available to remove contaminants from the waste stream, US EPA adopts effluent discharge guidelines and uses these guidelines to set the permit limits for the National Discharge Elimination System (NPDES) permittees. The original language of the CWA encouraged the use of “Best Available Technology” (BAT), “Best Conventional Pollution Control Technology” (BCT) and “Best Practicable Control Technology” (BPT). The use of “best” terminology to qualify prescribed technologies allowed for some flexibility in the interpretation of the various needs and standards of different industries, and to allow for consideration of costs and effluent reduction benefits in the permit decision-making process.

Water Quality Standard Planning

The second approach takes into account the environmental and social context of the receiving natural water body. Depending on the desired uses of the water body, states set water quality standards (WQS) for the natural water body. States develop priority lists for impaired waters (303(d) lists) and set Total Maximum Daily Loads (TMDLs) for specific pollutants (US EPA, 2014). The two complementary approaches of NPDES and TMDLs are designed to work together so water quality goals are linked to permit limits. If a given water body is not meeting its water quality goals, this may lead to more stringent NPDES permit limits. The dual approach also implies that NPDES permits, which are issued to point sources, cannot capture all sources of pollution, especially nonpoint source pollution, which are difficult to attribute to a single, discrete source. TMDLs are meant to ensure that impaired water bodies are still held to set water quality standards.

Today, these two approaches in the CWA can be understood as approaches to regulating "point" and "nonpoint" sources. Of the two approaches, the technology-based, NPDES permitting approach is often associated with the regulation of point sources. Point discharges in violation of NPDES permit effluent limits are subject to fines or mandates for injunctive relief via administrative judicial action. The following are regulated as point sources: industrial effluent, wastewater treatment plants, concentrated animal feeding operations (CAFOs), combined sewer systems (CSS), and municipal separate storm sewer systems (MS4s). All other sources are designated as "nonpoint" sources. Although this dichotomy between "point" and "nonpoint" sources is still commonly used today, it is not only not reflective of physical pollution generation processes, it is also a hindrance to transfer of successful lessons learned from those sources categorized as "point" to "nonpoint" and vice versa.

Current practices are already incorporating more ecological perspectives of system function into infrastructure management and regional planning practices. Both infrastructure management and regional planning would additionally benefit from an explicitly ecological perspective that bridges scales and sectors to better unite the two complementary halves of the CWA. In the following section, I suggest how the concept of "Green Infrastructure" within an ecological conceptual framework has already begun to bridge the gap, and how continued ecologically-framed research around GI will strengthen the power of the CWA to improve future water quality.

REGULATION OF POINT AND NONPOINT SOURCES OF WATER POLLUTION

Point source regulation has been based on economic theory

Point sources are sources of pollution that can be attributed to a discrete location in space. For example, the production processes of a paper mill produce wastes that are discharged in water from an outlet to a natural water body is regulated as an industrial point source of water pollution. Firms' decisions to comply with environmental regulation can be understood as a cost-benefit analysis where firms weigh the probability of enforcement and probable fines (Expected Marginal Penalty, EMP) and the marginal costs of implementing pollution abatement (Marginal Abatement Cost, MAC) (Gray and Deily, 1996; Dasgupta *et al.*, 2000; Shimshack and Ward, 2005; Gray and Shimshack, 2011). Economic theory dictates that firms comply with environmental regulation because of the fear of fines associated with noncompliance. Fines associated with noncompliance internalize the negative externalities of pollution, pushing firms to change their practices for the benefit of society, which would otherwise collectively bear the negative impacts of pollution.

Where environmental responsibility can be clearly assigned, enforcement of environmental regulation of point sources has been shown to motivate even firms that were not directly fined by regulators to comply with regulation (Shimshack and Ward, 2005). Once an enforceable environmental standard is set, there is also evidence that regulated entities will achieve higher states of compliance than required by regulation. Even in cases where threatened fines were less costly than abatement measures, noncompliant firms have been shown to be motivated at least towards partial compliance (Harrington, 1988).

Challenges in economics-based pollution source regulation

In contrast to traditional point sources, it is much more difficult to attribute a discrete location for nonpoint sources of pollution. Nonpoint source pollution is generated over large areas, such as agricultural land, or atmospheric deposition, and is usually associated with wet weather events, which result in precipitation that runs off of land surfaces, carrying excess nutrients, sediments, and other contaminants along with it into nearby streams, rivers and estuaries. The large area and wet weather-dependent nature of sources typically thought of as nonpoint result in much more complexity in regulation. It is more difficult to attribute responsibility to specific contributors of pollution because of the increased number of actors involved over large areas. In addition, there is an increase of temporal randomness (stochasticity) of discharge compared to more process-driven effluent discharges.

While nonpoint sources are usually portrayed as harder to identify, there is also evidence that the EMP/MAC model underlying point source regulation does not truly capture complexity of decision-making and context behind pollution and pollution prevention. The breakdown of the EMP/MAC model is more severe the more stochastic (unpredictable) and open the system. Even for industrial processes, which are relatively deterministic (known) processes, unpredictability of accidental discharge has been documented to be a major source of both regulatory challenge in enforcement and in firms' decision-making when weighing costs and benefits of compliance (Brännlund and Löfgren, 1996). For both industrial firms and publically-owned wastewater treatment plants (WWTP), firms often choose to "overcomply" with regulation due to factors not captured by the EMP/MAC model such as decision makers wishing to present a "green image" to customers, or response to corporate image, reputation, external community pressure concerns or shifting cultural norms (Downing and Kimball, 1982; Arora and Cason, 1995; Potoski and Prakash, 2005; Banduopadhyay and Horowitz, 2006; Prakash and Potoski, 2007), indicating that the "system" to be regulated does not have a clear boundary at the edge of the firm's internal processes, but also includes public pressure, community and reputation that extend beyond the firm's specific business. Given this, it is not surprising that both spatial heterogeneity and temporal stochasticity of emissions have been shown to break down the economic EMP/MAC model, even for sources of pollution normally classified as "point sources" (Banduopadhyay and Horowitz, 2006; Shimshack and Ward, 2008).

As discussed above, environmental regulation of the "command-and-control" flavor – issuing permits and enforcing compliance through inspections and fines – has generally been considered successful in regulating traditional point sources such as industrial firms and wastewater treatment plants. Yet, 53% of river and stream miles and 69% of lakes, ponds and reservoirs in the US remain classified as "impaired" (US EPA, 2015). US EPA has identified that "nonpoint" sources of pollution remain the major challenge to improvement of water quality. In studies from the Chesapeake Bay, researchers estimate that 44% of nitrogen and 65% of phosphorous loads to the Bay originate from agricultural land uses and 25-28% of nitrogen originates from atmospheric deposition (US EPA, 2010).

Both of these sources are not regulated as point sources and generate pollution over large, distributed areas.

In light of this, it is increasingly critical that environmental strategies incorporate the complexities of large area pollution generation, heterogeneity of actors, and temporal stochasticity. The next section traces the history of GI as an acceptable strategy to meet CWA requirements. The lessons learned from the implementation of GI as a best available "technology" to prevent point discharges from infrastructure systems can be extended to how large-area, distributed natural infrastructure may be successfully implemented to deal with even more spatially and temporally stochastic sources, such as agricultural and atmospheric deposition sources of pollution.

COMBINED SEWER OVERFLOWS AND GREEN INFRASTRUCTURE

GI in cities is an infrastructure-centric concept that uses often-vegetated, source control Best Management Practices (BMPs) to intercept, evaporate or infiltrate surface runoff before it reaches the underground pipe collection system. Its primary purpose is to reduce loading on existing conventional infrastructure systems. As of the 2012 Clean Watershed Needs Survey, 14 cities officially included budget line items for Green Infrastructure as part of their CSO elimination programs (US EPA, 2016). Today, the use of GI as an acceptable technology for CSO abatement seems commonplace, with cities such as Philadelphia even planning for a majority GI-based strategy to eliminate CSO events (Philadelphia Water Department, 2009). However, both the definition of a CSO as a source of pollution that could be regulated as a "point source" and GI as an acceptable "technology" for point source abatement were both ideas that evolved over time.

The Evolution of Large-Area Point Sources

The original 1972 CWA did not specifically address CSOs, industrial storm runoff or municipal storm drains, but did explicitly exempt agricultural stormwater discharge from having to obtain technology-based discharge permits (US EPA, 2001). It was not until the 1980s that the initial focus of the CWA on traditional POTW and industrial point sources shifted to wet weather sources of pollution. In order to regulate CSOs as point sources, additional federal leadership and interpretation was needed to clarify how such point sources should be regulated. In 1980 an important case *Montgomery Environmental Coalition vs. Costle*, affirmed the EPA's interpretation that CSOs were not equivalent to discharges from WWTPs and thus not subject to limits based on secondary treatment standards placed on WWTPs. However, this ambiguous ruling could be interpreted to mean that CSOs were not *point* sources and did not need to be regulated to the same rigor as WWTPs and industrial point sources had been.

By the late 1980s, Congress and the EPA could not ignore the contribution of wet weather-dependent sources of water pollution. In 1987, the Congress passed another major amendment to the CWA, the "Water Quality Act of 1987, which created the "Nonpoint Source Management Program (Section 319 in the CWA) to give grants to states to support demonstrations, technology transfer and technical assistance to manage sources of pollution not explicitly regulated as point sources. The 1987 amendment also explicitly stated for the first time that industrial stormwater discharges and MS4s must obtain NPDES permits for stormwater outfalls. This decision explicitly extended the classification of "point source" to include stormwater generated over vast areas discharged at discrete points, even when such sources were not at all related to sewage collection, conveyance, or storage. The Water Quality Act of 1987 still exempted agricultural runoff from technology-based NPDES regulation, but funding was allocated to support further research on the contribution of agricultural runoff to water quality degradation.

Two years later, the EPA issued the National Combined Sewer Overflow Control Strategy in the Federal Register (US EPA, 1989). This document reaffirmed that CSO discharges *are* point source discharges independent of the POTW treatment facility. This clarification subjected CSS outfalls to NPDES permit requirements and required them to be brought into compliance with technology-based and water-quality-based requirements of the CWA. According to the strategy, “CSOs which are discharging without a permit are unlawful and must be issued permits or eliminated.” (US EPA 1989). The strategy stated some possible complexities for single, system-side permitting of CSOs and acknowledged that portions of a CSS are sometimes operated by multiple authorities and closely tied to the function of the treatment infrastructure of POTWs, recommending that NPDES permits should cross-reference the POTWs’ NPDES permit and effluent limits. At the time, it was not immediately obvious how the CSS outfalls should be considered point sources, since unlike other point sources, the systems contributing to CSO events covered massive urbanized areas, and were stochastically dependent on rainfall, groundwater levels (which would influence inflow and infiltration into the system) and domestic water usage rates within the city (which fluctuate diurnally, and affect the system’s ability to accommodate rain volumes). Although the strategy provided federal leadership on the interpretation and application of “point source” to CSOs, municipal organizations felt that the National CSO Control Strategy did not provide sufficient clarity and therefore they pushed the EPA for a consistent national approach to dealing with CSO events (US EPA, 1995).

The EPA responded by forming a Management Advisory Group in 1992, which included representatives from state and local government, industry associations and environmental groups. The result was the release of the CSO Control Policy in 1994, to expand upon the original strategy outlined in 1989. The 1994 CSO Control Policy required communities to implement two phases to bring CSOs into compliance with NPDES permits and water quality standards. Phase 1 required communities served by CSS to first implement the following Nine Minimum Controls (NMCs) no later than January 1, 1997 events (US EPA, 1995):

1. Characterization, monitoring and modeling
2. Public participation
3. Consideration of sensitive areas for prioritization
4. Evaluation of alternatives that will enable the permittee, in consultation with the NPDES permitting authority, WQS authority, and the public, to select CSO controls that will meet CWA requirements
5. Cost/performance considerations
6. Operational plan revisions that include long-term CSO controls
7. Maximization of treatment at the existing POTW treatment plant
8. An implementation schedule for CSO controls
9. Post construction compliance monitoring program to verify compliance

Phase 2 required communities to develop and implement Long-Term Control Plans (LTCPs) to ensure that the actions to be implemented would indeed lead to reduction of CSO events and improvement of water quality (US EPA, 1995). Compared to the original recommended controls in the EPA's 1989 Strategy, the 1994 Policy additionally emphasized *processes* of knowledge gathering, system understanding and acknowledgement of diverse stakeholders as opposed to emphasis on a singular permitted entity. These actions were all signs of recognition that BAT determination and evaluation under uncertain and more stochastic circumstances are much more difficult to ascertain, and for which there would not be a single "industry standard". The guidance of the 1994 policy essentially urged operators of wastewater collection and treatment facilities to broaden their understanding of the systems. Their previous NPDES permits covered the boundary of the process starting from the controllable inlet of the POTW, to the treated effluent outlet. Now, by nature of the much larger and weather-dependent system, they were being held responsible for a much more stochastic and heterogeneous system, including many processes which they had much less control over.

Development of Control Strategies

In its 2004 Report to Congress on the status of CSOs, the EPA presented numerous strategies for source control and system operations and maintenance distributed over the entire sewershed as viable technologies to attain compliance with NPDES permits for CSS outfalls. The Report presented real-time monitoring and model development as best practice technologies for reducing CSO events. This strategy departed from the previous understanding of “end of pipe” BATs, BCTs and BPTs that were deployed to physically treat or reduce flows at the outfall. The purpose of these tools was not to treat the physical flows themselves, but rather to identify problem areas within the watershed—problematic areas within the system that contributed to the downstream “point source” of the CSS outfall.

The 2004 report was the first time that EPA advocated the use of Low Impact Development (LID) as an acceptable treatment technology for CSO control. LID is a source control strategy that is meant to reduce the generation of runoff before it enters the collection system, usually using vegetated areas and infiltration of runoff into the underlying soil and slowing peak flows from overwhelming infrastructure capacity.

Wastewater utility operators suddenly found the systems for which they were responsible including not only the well-defined infrastructure assets of the POTW, conveyance structures and pump stations; the incorporation of source control BMPs and LID extended the boundary of their system to include land use type, development decisions, and management of stormwater runoff from private property. CSS and MS4 outfall discharge permit holders became large-area generated point sources. These permit holders are similar to the problem of diffuse generation, multiple-actor nonpoint sources of pollution in their limited control over the system and high stochasticity, but they are unique in their assigned accountability over discharge effluent quality. A major question for the operators of NPDES permitted systems (stormwater or wastewater utilities) was how to pass on accountability of the function of their systems onto the diverse, heterogeneous property owners and residents across their service areas that were producing the runoff feeding the system. As will be further addressed in the following section, while the 1994 CSO Control Policy effectively assigned accountability to stormwater and wastewater utilities to compel compliance with more stringent environmental standards, it is not clear that further passing on economic-based accountability to property owners and residents within the service area will actually result in the desired effect of greener land management practices, distributed reduction of runoff and system loading, and elimination of CSO events.

IDENTIFYING SOLUTIONS TO LARGE AREA-GENERATED SOURCES OF WATER POLLUTION

Problem of Accountability or Cooperation?

Some researchers have attributed the reason for stalled surface water quality improvement to the inability of regulatory actions to affect land use practices (Dyckman and Paulsen, 2012). Although the link between land use and water quality is undoubtedly clear, the US has historically rejected the idea of federal involvement in local land use decisions, a sentiment that was particularly apparent in the failure of the National Land Use Planning Acts of the 1970s (Rome 2001). There are two major schools of thought for the best way to correct for the gap in linked land use and water quality planning. These schools of thought have emerged in response to regional scale, integrated land-water management practices, but they also conceptually apply to land-water management practices within cities.

One approach, spearheaded by former Interior Secretary General Babbitt called for an increased, unified federal vision for land-use and water planning. Babbitt believed that federal funding should be contingent on approval of states' comprehensive, integrated land/water plans and would increase realization of outcomes (Babbitt, 2007). In contrast, others argued for more flexible institutional arrangements that are better able to deal with the fragmented nature of federalist government, including interstate compacts, interstate associations, federal-state partnerships, federal-interstate partnerships, or federal-state-local partnerships (such as Metropolitan Planning Organizations formed for transportation infrastructure planning). Such partnerships allow diverse locally-specific stakeholders to negotiate water quality trading agreements and set water quality standards given local conditions and means of achieving those water quality standards (Leach and Pelkey, 2001; Sabatier *et al.*, 2005; Mandarano *et al.*, 2008; Dyckman and Paulsen, 2012).

Assignment of greater accountability and federal oversight (e.g.: Babbitt, 2007) reflects the belief that greater accountability will result in clearer EMP/MAC tradeoffs, which would then result in the ability to nudge actors toward better environmental decisions.

One former EPA official expressed that in over 20 years of work in the water pollution regulation sector, he had never truly seen a source of pollution that could not be attributed to some point, indicating that accountability should not be thought of as fundamentally unknowable (Layzer, 2011). The history of how discharges from MS4 and CSS outfalls were not immediately clear from the start of the CWA, but were defined through federal leadership, highlights how accountability can be assigned to large-area-generated sources of pollution. Just as the heterogeneous landscape of the urban environment came to fall under the regulatory jurisdiction of MS4 and CSS outfalls, nonpoint sources could plausibly be conceived of as a point source at a larger scale. The question then is not necessarily about technical feasibility, but of whether hyper-focus on identifying point sources and applying EMP/MAC-type regulatory and economic incentives to those sources will actually result in the expected environmental outcomes.

For example, if driving produces emissions of NOx that contributes to the atmospheric deposition portion of nitrogen loading to the Chesapeake Bay, a point source-type policy response might be to issue emissions permits to each driver or use a vehicle miles traveled-based tax to discourage driving. However, such a strategy might not be socially equitable, since such a tax would be higher for those who live further from their workplaces – possibly a result of larger structural forces, including land-use patterns and urban economics, and potentially larger burden on poorer households. This simple example illustrates how environmental decision-making processes that affect diverse actors are likely to involve a host of other factors that increase the problem's complexity.

In contrast to the familiar point source EMP/MAP-based approach, more flexible arrangements based on negotiation, partnerships and communication (e.g.: Sabatier, 2005), reflect a belief in another approach to environmental stewardship: one that accepts complexity and interactions between system components and leverages these interactions to identify solutions. In the next section, I apply the concept of socio-ecological systems (SES) to stormwater management planning and policy.

Urban Ecology and Socio-Ecological Systems (SES)

Urban ecology has emerged as a unifying area of interest for natural and social scientists as well as designers and planners. Broadly, the study of ecology is defined as the interaction between an organism and its environment, where "environment" is in contrast to whatever biological complex is chosen (Tansley, 1935). Part of the appeal of the ecological concept is its ability to metaphorically adapt to the context to which it is being applied (Pickett *et al.*, 2004); however, a core requirement is identification of functional linkages between organisms and the environment of a physical area (Pickett *et al.*, 1997). Humans and human influences—including our social and cultural structures, institutions, and built infrastructure—are an important part of many physical and biological complexes, especially in urban areas. It is therefore useful to explicitly include human components of ecological systems (Tansley, 1935; Machlis *et al.*, 1997; Grove *et al.*, 2015).

Beginning in 1997, with the establishment of two National Science Foundation Long-Term Ecological Research sites located in the urban areas of Phoenix and Baltimore, conceptualization of an ecology *of* cities, in contrast to previous views of ecology *in* cities started to come into focus. Previously, scientists studied ecology *in* cities by using comparative before and after experiments or measurements along urban to rural gradients to quantify the effects of urbanization on natural systems and focused on the green spaces in cities as disturbed rural analogs to the ‘natural’ condition. In contrast, these urban LTERs took the ecology *of* cities approach, which emphasized incorporation of whole systems—social and biophysical—to understand how cities metabolize material and energy flows (Grimm *et al.*, 2000). Framing the city as an ecosystem, and a unit of analysis in itself resulted in a “radical expansion” of ecology (McDonnell and Pickett, 1990; Grimm *et al.*, 2000).

Within the urban ecosystem framework, the role of humans, human institutions and social relationships and their interrelations with biophysical resources are identified more explicitly for research. The “Human Ecosystem Model” (**Figure 2.2**) portrays an example of the potential relationships between system components (Pickett *et al.*, 1997). Within the ecosystems, patterns and processes highlight the roles of change over time and spatial patchiness of heterogeneity that are present within self-organizing systems such as cities.

The research resulting from two decades of this conceptual framework of urban ecology has succeeded in identifying previously unexplored gaps and connections in knowledge, debunking previously held conceptions about the ecological processes in urban areas, and has contributed to constructing a unified theory of urban ecology (Pickett *et al.*, 2008). Conceptual frameworks from urban ecology are useful for addressing complex socio-ecological systems by promoting interdisciplinary research, and translating and disseminating results. In the human ecosystem model, components of the human social system, such as regulations, social norms, and knowledge, influence our planning for resource systems. Resource systems, which include cultural, socioeconomic and ecological resources also in turn influence human social systems.

Related to urban ecology is the idea of socio-ecological systems (SES). Systems science is the "study of an interconnected set of elements that is coherently organized in a way that achieves something" (Meadows, 2008). Undoubtedly, SES are related to urban ecological concepts, but additional emphasis is placed in *purpose* in addition to *pattern* and *process.* The identification of the purpose of the system underlies the importance of identification of the interconnections between the elements of the system. The interconnections and feedbacks determine a system and its sustainability. The feedbacks between ecological and social components of the system are what allow us to properly allocate and protect limited resources for the longevity of society (see **Figure 2.2**).

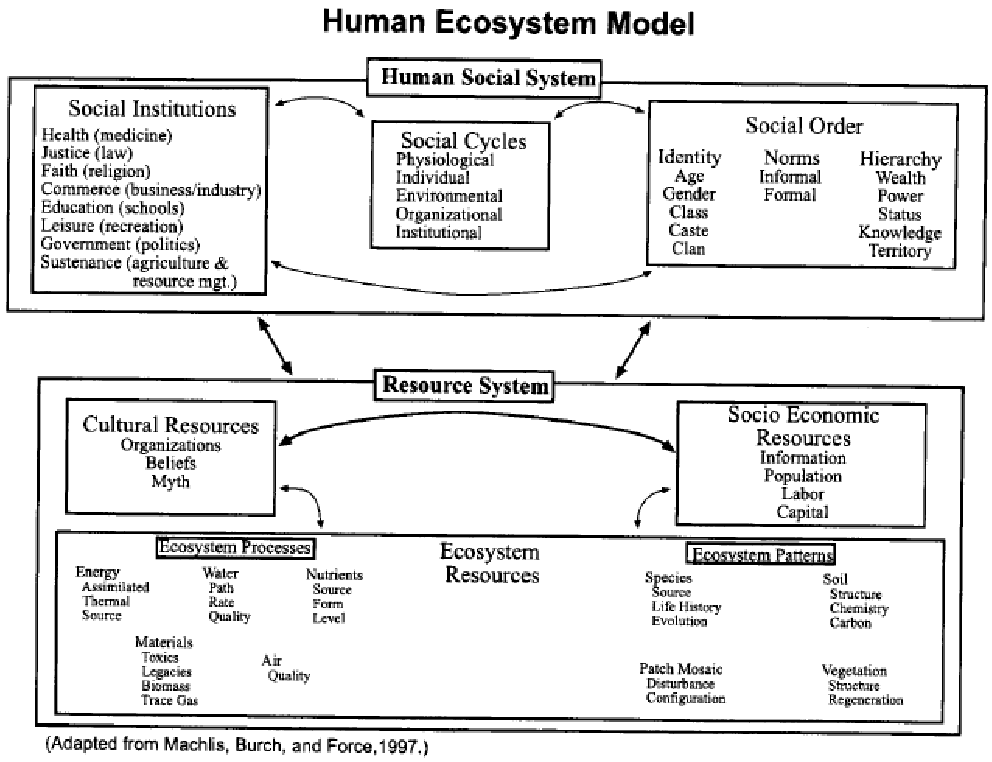

Figure 2.2. An example of a socio-ecological system conceptual model representation: the Human Ecosystem Model. Source: Pickett *et al.* 1997

Perhaps the best-known example of unsustainable feedback between social system allocation and environmental resources is the "Tragedy of the Commons." According to the theory of the Tragedy of the Commons, a failure for social institutions to incorporate the negative externalities of common pool resources, leads to resource overuse. The marginal benefit that any one actor gains from overusing the resource outweighs the cost that is spread across all actors (Hardin, 1968). Based on this theory, people with a common-pool resource will tend to pollute or overuse that resource until it eventually collapses (the system is over-logged, over-fished, or completely degraded). The typical response to the tragedy of the commons is to internalize the negative externalities associated with pollution or overuse. Negative externalities can therefore be understood as a lack of recognition of property systems. Theoretically, no actor would willingly pollute or unsustainably harvest resources if he/she were to bear the total cost of doing so. The answer to the tragedy of the commons problem then has been to internalize the negative externality by assigning property rights or by imposing Pigouvian taxes meant to reduce pollution and overuse (Pigou, 1920; Coase, 1960). However as alluded to above, such simple frameworks and the imposition of these policy solutions frequently fail. Within a SES framework, failure occurs when the *purpose* of the system, to sustainably support society with natural resources, has been lost. The goal of a whole systems perspective is to identify more elements of the system contributing to its overall purpose, not to simplify the system into one-size-fits-all rules.

In addition to the dominant paradigm of internalizing negative externalities through market signals as a solution to common-pool resource problems, there are also examples of long-term sustainability achievement through communication and self-organizing groups (Ostrom, 2009). Therefore, especially when Pigouvian tax-type policy responses fail to solve a complex environmental problem or to explain actors' behaviors, it becomes necessary to incorporate more specific components of the complex system, to understand their intersections and relationships, rather than ignore or assume away complexity. Ostrom and others have suggested multi-level aspects of complex SES that can improve a system's ability to self-organize sustainable management and use of a common pool resources. The framework includes the overarching social-economic and political setting (e.g., economic development, demographic trends, media organization), resource systems, resource units, governance systems, user characteristics, interactions between users, outcomes, and related ecosystems. Both conventional gray stormwater infrastructure and green infrastructure can be understood as part of a larger SES in addition to merely an example of the Tragedy of the Commons.

It is the acknowledgement of stochastic, open-system dynamics that makes the socio-ecological conceptual model of infrastructure increasingly relevant in 2017. Currently, some of the components of the ecological view of infrastructure are already being incorporated into infrastructure management and urban planning practices. Others, are understudied.

Urban Runoff as a Socio-Ecological System

Stormwater flows and storage volumes in conventional infrastructure within an urbanized area can be understood as common-pool resources because water quality and available storage diminish as runoff flows through the urban environment (Flynn and Davidson, 2016). In the US, the regulatory context of the Clean Water Act combined with local public works and environmental agencies' desires to improve infrastructural and environmental function have resulted in the enactment of standards related to the management of stormwater. As Ostrom suggests however, the problem of pollution associated with urban runoff is not likely to be solved simply through enacting a property-rights based system, or Pigouvian tax penalty for runoff pollution. Cities exist within a complex SES with embedded socio-economic realities, governance structures, and legacy infrastructures and institutions. Increasing fines on local utilities already burdened with aging infrastructure costs for example, is neither a fair decision, nor one that is likely to be effective or even feasible. The local decision and financial capacity to upgrade aging infrastructure systems, especially in older, post-industrial "legacy cities" in the US, requires innovative planning, and partnerships at multiple levels of government, with communities, local nonprofits, community organizations and philanthropic groups (Birch and Wachter, 2008). The multiple benefits of GI allows local communities to find creative ways to partner to achieve their CWA mandates, improve environmental and infrastructural function, and improve livability. For areas experiencing growth, this can be mandated through new compelling development to meet rainfall retention standards. But, it is more of a challenge for cities with slow redevelopment rates, falling or stagnated population growth, aging infrastructure, and significant financial constraints, a perfect storm for many of America's legacy cities (Schilling and Logan, 2008).

The decision to adopt formal GI planning as part of a city's capital improvement plan is situated within an SES framework that includes complex operational choice rules, such as regulations, funding, and management plans. There are also potentially competing ordinances involving zoning, subdivision regulations, and building codes that can prevent successful GI implementation (Flynn and Davidson, 2016). The barriers to city-wide adoption of GI planning are well-documented. "Siloed" local government departments can make necessary collaborations to implement GI plans difficult (Brown, 2005). Centralized technocratic culture often prevents effective management of distributed infrastructure systems (Roy *et al.*, 2008; Dhakal and Chevalier, 2016). And, many cities' are dealing with limited infrastructure budgets and declining populations that limit any local investment in infrastructure and foster public pushback to increasing fees (Keeley *et al.*, 2013).

Even within cities that have adopted formal GI plans, there still exist major barriers to successful implementation. The most ambitious GI plan in the US, Philadelphia's *Green City, Clean Waters* program, aims to treat one third of its impervious area (10,000 acres) with GI to reduce loading to its overburdened combined sewer system by 2035. Since GI is land-area intensive, the plan would benefit greatly, and in fact requires, the participation of private commercial property owners to treat their stormwater on site to meet this goal (Philadelphia Water Department, 2009). In the spirit of internalizing the negative externality of runoff production, in 2009 Philadelphia changed its stormwater billing to be based on impervious surface area, rather than on water meter usage. If property owners willingly treated runoff on their properties or reduced imperviousness, letting it infiltrate into soils instead of loading the public sewer infrastructure, the Philadelphia Water Department (PWD) would credit their accounts (Valderrama and Davis, 2015). This market incentive was meant to send the correct environmental behavior "nudge" to encourage private adoption of GI, but has had limited effect (Hsu *et al.*, 2017).

The distributed nature of GI can be understood as both an opportunity for the 'democratization' of formerly centralized, technocratic planning practices, and as a challenge. For example, the West Mill Creek Project, a decades-long collaborative community program organized educational, community activities, and civic leadership programs around issues of stormwater management in Philadelphia. The West Mill Creek, a historical stream that was sewered and buried in order to accommodate the city's grid-based street network, was the focal point. Issues of environmental justice, geospatial mapping, public green space, and lot vacancy all intersected with how water drained from this urban watershed (Spirn, 2005). In contrast to technocratic, top-down infrastructure planning paradigms of the past, this civic political model emphasized the importance of place, organizing diverse coalitions of activists to address overlapping community issues, including: economic growth, environmental quality, local government control, and education. For example, part of the program paired university students with local public school students in Action-Based Learning about urban environmental science and technology related to the buried stream. Instead of simplifying and siloing, this model created transformation by including deliberation of various interconnections between system elements (Karvonen, 2011). The creation of knowledge, expertise and even data products from the West Mill Creek project has made long-term socio-ecological impacts that would be difficult to quantify by simplifying the system to singular metrics (for example: reductions in gallons of CSO discharges). Examples of these socio-ecological impacts include: development of remotely sensed land cover and topographic data products for the City of Philadelphia and the initial training of local high school and graduate students who later went on to innovate in urban stormwater management geospatial software, web applications and land vacancy planning programs in Philadelphia and Baltimore (Spirn, 2005) [1]. These are examples of dispersed beneficial contributions to the overall "ecosystem" of distributed stormwater management practices.

However, there is also evidence that the legacies of the past paradigm of top-down governance still casts a shadow over ideal democratic deliberation and participation in Philadelphia's *Green City, Clean Waters* program. Issues of inequality and distrust among residents and between residents and government officials have been shown to prevent true democratic deliberation (Travaline *et al.*, 2015). PWD's CWA mandate to implement greened acres places pressure on residents to accept the GI approach, leading to perceptions that efforts to "revitalize" their neighborhoods with GI had gone through little actual community participation. While distributed GI could represent a democratization of infrastructure, it might also be understood as an extension of top-down planning practices, also incorporating neighborhood aesthetics, and even land management practices on private properties. This balance is related to deeply entrenched relationships between various populations within the diverse urban environment and urban policy. True collaborative relationships under a mandated imperative to meet federal environmental regulation would benefit from lessons learned from past collaborative watershed-based initiatives.

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[1] Robert Cheetham, CEO of Philadelphia's largest geospatial software design company Azavea, is a former graduate student participant of the West Mill Creek project (1996-1997). Azavea has built geodatabases and tools to support the Philadelphia Water Department's deployment of GI (http://web.mit.edu/4.243j/www/wplp/about.html). One of the principal developers of Baltimore's *Green Pattern Book* for vacant lot planning, Mark Cameron, previously participated in the West Mill Creek project (1990-1991).

Watershed-Based Strategies and Green Infrastructure

Much has been written about collaborative approaches to watershed management. Collaboration is well-based in planning, which needs ways to deal with complexity and “wicked problems”, a term particularly apt within pluralistic societies in which there does not exist any indisputable public “good” or “optimal solution” (Rittel and Webber, 1973). Communicative rationality is the idea that knowledge is created through the exposing of contradictions, and negotiation of intents (Innes and Booher, 2010; Healey, 2012). Participatory planning decreases distrust between actors, leading to more consensus. Sabatier *et al.* (2005) empirically analyzed the conditions under which successful watershed partnerships have formed. The authors found that large ideological differences between participants were less likely to lead to the emergence of institutions of collaborative watershed management. Smaller, more stable, and more homogenous communities were more likely to lead to watershed partnerships accentuating the difficulty of planning for GI in highly heterogeneous urban environments (Sabatier *et al.*, 2005; Lubell *et al.*, 2009). Lubell *et al.* (2009) found the strongest predictors of partnerships were fairness, social networks, trust, budget support and scientific analyses.

The voluntary adoption of environmental best management practices among orchard growers in an agricultural watershed is a function of local networks that diffuse innovation, social capital and cultural change (Lubell and Fulton, 2008). These studies concede that the most difficult, even impossible, outcome of successful watershed partnerships to measure, however, is water quality outcomes, because of the long time-series water quality monitoring data necessary to determine change, and the impact of random factors such as climate and weather conditions. Instead, measurement of success of watershed-based planning usually relies on perceived impacts and other process-based or intermediary outcomes such as trust and communication (Carr *et al.*, 2012). Consensus building, negotiation and trust-building are important for large-area, multi-actor watershed management planning because they are more likely to result in specific restoration projects and in participants that are more likely to honor agreements (Sabatier *et al.*, 2005). They are also likely to have non-direct effects towards overall cultural changes, awareness and education and therefore should also be valued for reaching beyond narrow evaluations of collaborative programs (Leach *et al.*, 2002; Mazmanian and Kraft, 2009; Carr *et al.*, 2012). Estuaries involved in the National Estuary Program network have been shown to span more levels of government, integrate more experts and science into policy and fostered stronger interpersonal relationships (Schneider *et al.*, 2003). This is especially important in the context of local water infrastructure planning, which has been shown to include little vertical or horizontal integration beyond local engineering departments, impeding long-term perspective on infrastructure planning (Lienert *et al.*, 2013).

The concepts and benefits associated with large-area, land based and watershed-scale water pollution control strategies above need not be excluded from the strategies employed by sources that are already currently regulated as “point sources” within the CWA framework, precisely because point sources such as CSO and MS4 outfalls also incorporate many of the same complexities as sources typically thought of as “nonpoint” sources. There is much potential for participatory planning and inclusion of multiple objectives *within* urban areas, whose infrastructure systems have traditionally been governed by technocratic, command and control engineering. The concept of “civic politics” represents a shift from this view of urban systems to a more relational perspective between humans and nonhumans (Karvonen, 2011). Civic politics is more than decentralizing environmental policy. It is actually about “creating transformative mode of local politics steeped in in deliberative democracy and community activity” (Karvonen, 2011).

Participatory planning has educational value and increases the likelihood of goal attainment through collective action. Communicative rationality is the process of revealing patterns in what might initially appear like randomness, a step in environmental regulation that is necessary for all sources of water pollution, including CSOs and MS4 outfalls and everything located to their right on the spectrum.

In conclusion, there is an opportunity for urban GI planning to incorporate the findings, values and techniques of larger-scale watershed-based collaborative, voluntary and participatory planning. These techniques acknowledge and incorporate larger social processes of communication, education and cultural change into their long-term visions for environmental improvement, aspects that are certainly important for improving the function of urban infrastructure as well. However, others have expressed concern with the lack of accountability in results associated with collaborative watershed planning.

SES RELATIONSHIP TO PHYSICAL FUNCTION

There is also uncertainty around the physical hydrological performance of GI as a network. "Networks" of GI should be understood as integrated plans that incorporate the multiple scales and the contexts of the ecosystem services they provide (Benedict and McMahon, 2006; Rouse and Bunster-Ossa, 2013). As I stated above, the idea of GI refers to both the "greening" of conventional infrastructure, and the "infrastructuring" of green-ness, or natural land. Therefore GI includes engineered best management practices—rain gardens, pervious pavement, etc.—that intercept stormwater runoff before it enters conventional drainage infrastructure. It also refers to the regional conservation of natural lands alongside development. Both involve issues of environmental and infrastructural governance, local and regional land use planning, and the linked management of land and water resources by many actors.

Questions of effectiveness of GI within these contexts and scales should not be considered separately. “Effective” physical planning and functioning of GI requires scientific understanding and definition of the physical hydrologic processes that determine how water moves through and is distributed in the environment. This requires us to not only account for surface runoff as is typically the focus of urban hydrological models, but processes of infiltration, flows though the unsaturated and saturated groundwater zones, and evapotranspiration. Evidence of these processes at different spatial and temporal scales help us identify important thresholds, feedbacks, interactions and unexpected outcomes from the ecosystem services we expect from GI, the “purposes” of this SES. Currently GI is in an experimentation phase. Measurements of physical effectiveness of GI will inform how we adapt our infrastructure, land, and water planning and management practices to meet environmental goals. But *how* we go about correcting course when goals are unmet, and *how* we choose to iteratively adapt our infrastructure, land, and water management techniques and policies, which levers we choose to pull, will be based on how we understand the dynamics of the components of the GI and urban runoff SES now. As I have touched on in this chapter and will continue to explore in the coming chapters, the dynamics and components involved include the social processes of GI adoption and urbanization and the physical processes that affect hydrological response.

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CHAPTER 3: BEYOND IMPERVIOUSNESS: HYDROLOGIC RESPONSE AT THE REGIONAL WATERSHED SCALE

INTRODUCTION AND BACKGROUND

Research has long shown the link between urbanization and degraded water quality and aquatic habitat (Hammer, 1972; Hatt *et al.*, 2004; Newall and Walsh, 2005). For managers of urbanizing watersheds, one key indicator of negative hydrological change has been impervious surface area. Instead of subsurface flows that are typically the dominant response to rain events in humid catchments, the hydrologic response in urbanized watersheds becomes dominated by surface runoff (Leopold, 1968; Arnold and Gibbons, 1996). Increased surface runoff occurs when impervious surfaces in the form of roofs, parking lots, roads and sidewalks prevent precipitation from infiltrating to the underlying soil. The result is a "flashier" runoff-response, which leads to flooding and erosion and sedimentation of natural water bodies (Booth and Jackson, 1997; McBride and Booth, 2005).

Impervious surface area has emerged as a key indicator of impaired aquatic habitat for watershed managers and urban planners for its ease of conceptual understanding, but research has shown that impervious surface area alone is not sufficient for understanding underlying mechanisms of hydrological response and degradation (Harbor, 1994; Brabec, 2002; Shuster *et al.*, 2005). One key distinction when trying to quantify impervious surface is the functional difference between Total Impervious Area (TIA) and Effective Impervious Area (EIA). Underlying the concept of EIA is the idea that degree of connectivity of impervious surface area is important in addition to the total magnitude of impervious area (McBride and Booth, 2005; Shuster *et al.*, 2005; Alberti and Booth, 2007; Moglen and Kim, 2007). Emphasis on hydraulic connectivity implies that pervious surfaces could also function similarly to impervious surfaces and hydrologic response is dependent on antecedent moisture of underlying soils, slope and connectivity to impervious surfaces. Alternatively, impervious surfaces that are not hydraulically connected to the drainage network may not be considered EIA. This latter concept is the principle behind run-on infiltration stormwater management techniques in urbanized areas, which aim to "disconnect" impervious areas, reduce peak flows and volumes, and increase baseflows to local streams (Miles and Band, 2015).

Researchers have approached quantifying EIA from TIA in different ways, including using empirical conversion factors, field surveys, and sensitivity analyses, but there is general agreement that EIA, rather than TIA more closely represents the physical process of hydrological impact on flow regimes (Alley and Veenhuis, 1983; Dinicola, 1990; Booth and Jackson, 1997; Brabec, 2002; Shuster *et al.*, 2005; Knighton *et al.*, 2013; Palla and Gnecco, 2015). Hydraulic connectivity has not only been shown to be one of the most sensitive parameters in urban hydrological modeling, resulting in modeled peak discharge variations of up to 265% in some cases (Lee and Heaney, 2003). It is also among the parameters estimated with the most uncertainty in urban hydrological modeling (Moglen and Kim, 2007; Knighton *et al.*, 2013). Others have suggested that overemphasis on connectivity of impervious area (EIA vs TIA) detracts from important changes to soil porosity, vegetation, imported water and other water infrastructure that urbanization has on hydrologic response and catchment water balance (Brandes *et al.*, 2005; Meierdiercks *et al.*, 2010a; Hamel *et al.*, 2013).

In this chapter, I do not assume impervious area as the dominant causal factor for flashy hydrologic response. Instead, I develop a robust statistical methodology to classify urban catchments into two groups. The first group includes catchments that have retained incremental storage exceedance, a natural condition for catchments in humid climates that hydrologists refer “Variable Source Area” (VSA). The second group includes catchments that have lost incremental connectivity and instead exhibit constant hydraulic connectivity. Based on the classification, I address the following questions:

1.) How does undeveloped land compare to land development variables in explaining the presence of VSA-response?
2.) How does a higher fraction of developed (low density) open area in urban areas influence VSA?
3.) How does stormwater management infrastructure, such as proximity to a combined sewer outfall, or presence of detention/retention-based stormwater management guidelines affect the probability of VSA-response?

This study contributes to the existing literature by providing empirical evidence of the development-specific characteristics associated with VSA-type response using a cross-section analysis of 119 unique urbanized catchments.

URBAN VARIABLE SOURCE AREA

The Hortonian model of runoff generation posits that runoff occurs when infiltration rates are exceeded by rainfall intensities. This differs from runoff generation in humid regions, which occurs by subsurface storm flow and saturation excess overland flow (Dunne, Horton and Black, 1970; Dunne *et al.*, 1975; Dunne, 1978). Consideration of antecedent soil moisture and differential contraction of saturated areas between storm events led to the “variable source area” (VSA) concept of runoff generation. VSA emerged as an important model describing event-to-event, non-constant runoff contributing areas in undisturbed humid regions (USFS, 1961; TVA, 1965; Hewlett and Hibbert, 1967; Dunne *et al.*, 1975).

Subsequent empirical research has shown that site-specific conditions such as high soil conductivity, steep slopes, mid-slope or downslope positions within the watershed and seasonality affect presence of the VSA condition (McGlynn and McDonnell, 2003; Jencso *et al.*, 2009). In mountainous, alpine forested and agricultural catchments, runoff is first generated in riparian zones, and riparian-hillslope connectivity increases under wetter conditions (McGlynn *et al.*, 2004; Ocampo *et al.*, 2006; James and Roulet, 2007; Wenninger *et al.*, 2008). Monitoring patterns of soil moisture spatial extent has shown a clear thresholding relationship between antecedent wetness and rainfall and storm runoff (Detty and McGuire, 2010; Penna *et al.*, 2011). Event-based rainfall runoff ratios also support threshold relations in subsurface stormflow and that subsurface flow is a dominant source of runoff (Tromp-van Meerveld and McDonnell, 2006). While the VSA model has been called into question for its ability to apply to all situations (McDonnell, 2003), it still remains attractive for its ability to conceptualize non-constant ratios in the rainfall-runoff transformation.

In the study of urbanized catchments, land-use change and other human modifications to catchments has resulted in both better identification of specific processes and confounded sources of observed non-constant contributing area and thresholding effects. There has been significant interest in examining the effects of impervious surface area, infrastructure and developed open space associated with urbanization on increased hydraulic connectivity at the catchment scale. Placement and configuration of imperviousness within a catchment can have a significant influence on downstream response (Mejía and Moglen, 2010). Locations and configuration of conventional conveyance (Tague and Pohl-Costello, 2008; Meierdiercks *et al.*, 2010a; Ogden *et al.*, 2011), infiltration-based (Gobel *et al.*, 2004; Easton *et al.*, 2007; Miles and Band, 2015) and detention-based (Smith *et al.*, 2015) stormwater management infrastructures also influence incremental connectivity in hydrologic response of a catchment under varying event depths.

Contrary to commonly held beliefs about limiting imperviousness of development in order to avoid negative changes in hydrologic regime, studies indicate that developed open space can also have limited ability to prevent flashy response. Reasons for this include the limited infiltrative capacity of compacted soils (Smith and Smith, 2015), high proportion of runoff response attributed to shallow subsurface flow under residential lawns (Wigmosta and Burges, 1997), subsurface saturation due to leaky water distribution infrastructure (Lerner, 2002), and decreased evapotranspiration associated with vegetation change (Bhaskar *et al.*, 2015). **Table 3.1** shows an adaptation of the VSA to include urban run-on from impervious areas and other potential sources of impacts to soil saturation in urbanized catchments (Miles and Band, 2015). As shown in **Table 3.1**, urban VSA response is associated with incremental connectivity of conveyance infrastructure, impervious areas, and soils and pervious areas.

Table 3.1 Comparison of Theories of Runoff Generation: Hortonian, VSA and Urban VSA

	Hortonian	**Dunne's Variable Source Area**	**Urban Variable Source Area**
Theory	Runoff occurs when infiltration rates are exceeded by rainfall intensity	Runoff occurs when hydraulic connectivity is reached. It is a function of infiltration and differential contraction of saturated areas	Runoff occurs when hydraulic connectivity is reached. It is a function of infiltration and differential contraction of saturated areas

Main Drivers	Land surface cover, soil infiltration properties	Vegetation's ability to recover capacity of soil, slope, sag points within catchment, surface-subsurface interactions, hydraulic conductivity	Vegetation's ability to recover capacity of soil, slope, sag points within catchment, surface-subsurface interactions, hydraulic conductivity, connectivity due to infrastructure, run-on infiltration from impervious surfaces onto pervious surface areas

Analyses of empirical rainfall-runoff relationships from urbanized catchments have revealed that for smaller storms (< 38.1 mm or 1.5 inches), runoff depths as a fraction of the rainfall depths correspond closely to the EIA of the catchment. However, this relationship is less reliable for larger storms (Doyle and Miller, 1980). Regression-based analyses of the relationship between rainfall and runoff depths have been used to delineate the sequentially gained hydraulic connectivity of EIA, TIA and pervious areas respectively and to estimate their proportions within the catchment area (Boyd *et al.*, 1993, 1994; Goldshleger *et al.*, 2012; Loperfido *et al.*, 2014; Ebrahimian *et al.*, 2016). Studies which examine changing ratios between rainfall depth and runoff depth within a catchment all share a common interpretation that the variable proportion of area contributing to the hydrologic response is dependent on the total depth of rainfall.

In this chapter, I determine the significant predictors of VSA hydrologic response across urbanized catchments using regression analysis. Previous studies suggest that both impervious surface and land development in general (including seemingly pervious areas) will result in the dominance of Hortonian flow over VSA, while lower levels of development will result in the dominance of VSA over Hortonian overland flow (Miles, 2014). In urbanized catchments with high levels of impervious surface, we expect the contributing area from these catchments to correspond to the fraction of the catchment area that is composed of impervious area.

In VSA-dominated catchments, we would expect a nonlinear relationship between rainfall and runoff. As rainfall depths increase or rainy periods are prolonged, we expect some areas within the catchment area to incrementally lose capacity to store and infiltrate precipitation as storage thresholds are exceeded. This will lead to an increasing slope in the relationship between rainfall and runoff as cumulative rainfall depths increase. It should be noted that the conceptualization presented in this work (**Table 3.1**), departs from the Dunne VSA model in that it includes both runoff production processes (saturation excess and infiltration excess) and other factors specifically of interest in urbanized catchments that influence observable nonlinearity at discrete downstream streamflow measurement locations, such as the presence of CSS or other stormwater management infrastructure.

METHODS

Broadly, my methodology involves three steps. First, I perform hydrograph separation to create a dataset of paired event rainfall-runoff depths for each catchment in the analysis. Second, I develop a statistical methodology to detect the presence of nonlinearity in the rainfall-runoff relationship for each of the catchments, using the rainfall event data. Lastly, I use logistic regression to estimate the effects of the catchments' characteristics on VSA-type response.

Data

National-Level Datasets

Catchments for the analysis were selected from stream gauge flow monitored by the USGS, with characteristics included in the GAGES II database. GAGES II was developed by the USGS to provide users with an exhaustive set of geospatially-specified catchment characteristics corresponding to a large number of gauged watersheds. The database includes both “reference” watersheds, which are minimally influenced by human activity, and watersheds that represent a range of hydrologic conditions including urban development intensity (Falcone *et al.*, 2010). For a catchment in the national-level dataset to be included in this study, I used three criteria. First, the catchment had to be at least 50% developed according to the National Land Cover Dataset urban development classification. Second, the stream gauge had to be located within a 15-mile radius of an airport-based precipitation gauge having hourly data. Third, the catchment had to have at least 35 rainfall events that resulted in paired rainfall-runoff data. Stream gauge data for GAGES II catchments were downloaded from the USGS website (http://nwis.waterdata.usgs.gov/nwis/sw) using basin identification numbers and date ranges for available flow and precipitation data (Lins, 2012). Precipitation data was obtained from the National Climatic Data Center (http://www.ncdc.noaa.gov/). From these criteria, the study included 91 analysis catchment areas in the contiguous US (shown in **Figure 3.1**).

The catchments ranged from 50.49% developed to 99.98% developed. The median level of development was 84.37%. The 30-year (1970-2000) average annual precipitation among the study basins ranged from 63.31 cm to 136.80 cm. The drainage areas ranged from 3.70 km^2 to 505.80 km^2 with a median drainage area of 85.06 km^2. The generalized rainfall intensities in centimeters per hour for a 2-year, 1-hour storm event ranged from 4.06 cm (1.6 inches) per hour to 5.59 cm (2.2 inches) per hour.

I added three variables to those in the GAGES II database: (1) distance of the stream gauge location to the nearest (upstream or downstream) active combined sewer outfall; (2) whether the watershed included a community served by a CSS; and (3) a binary variable for whether the city or county in which the stream gauge was located encouraged infiltration, retention, or detention-based stormwater management practices at the time of the study. Geospatial locations of permitted outfalls were extracted from the EPA's Facility Registry Service (http://www.epa.gov/enviro/facility-registry-service-frs) for all permitted combined sewer outfalls listed by EPA (US EPA, 2004). Promotion of stormwater management practices was determined through an internet search of the name of the city and county in which the gauge was located, followed by the terms "Stormwater Detention, Retention, Green Infrastructure, Infiltration." Locations for which informational materials were readily available were presumed to be "actively" promoting this type of decentralized infrastructure.

Because CSSs have the potential to confound the results of the VSA classification analysis, I subset the national-level dataset with gauges known to not include any combined sewer systems. Of the 91 national-level catchments, 56 were confirmed not to have CSS within their boundaries. This subset is hereafter referred to as the "non-CSS dataset" (shown in **Figure 3.1**).

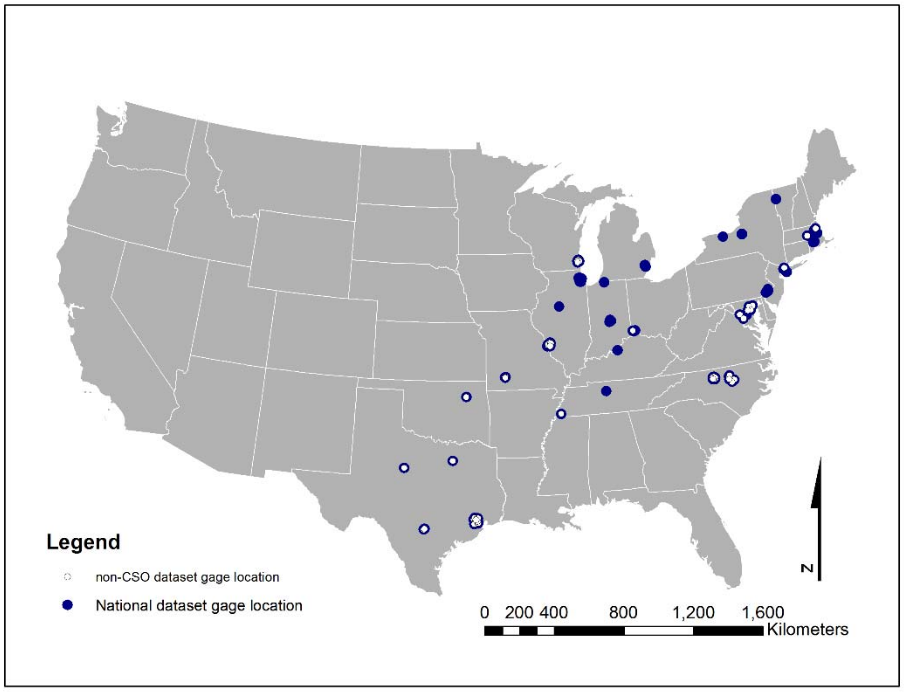

Figure 3.1. Locations of national dataset and non-CSS dataset analysis catchments

Batlimore Metropolitan Area (BMA) Datasets

The question of spatial heterogeneity in rainfall records was one of the major concerns with the analysis of the national dataset. Others have shown that especially in urbanized areas, where human activity and changes to the natural landscape influence micro-climates and local weather patterns, precipitation measured at one discrete location can vary significantly from the amount of rainfall at another nearby rain gauge (Shepherd, 2005; Smith *et al.*, 2012). For this reason, the analyses were also performed on a dataset of Baltimore Metropolitan Area (BMA) basins for which there was HydroNEXRAD radar precipitation data available covering the entirety of the gauge's catchment area. Radar rainfall data processed by the HydroNEXRAD system was obtained at a 1 square kilometer resolution at 15-minute intervals. A multiplicative bias correction value was then used to bias correct basin average time series data for each basin for each 15-minute time period to calibrate HydroNEXRAD data to precipitation records from a diverse network of rain gauges in the Baltimore region (Smith *et al.*, 2012). This procedure allowed for the use of spatial precipitation records that fell over the contributing area and should be much more accurate than discrete rain gauge data.

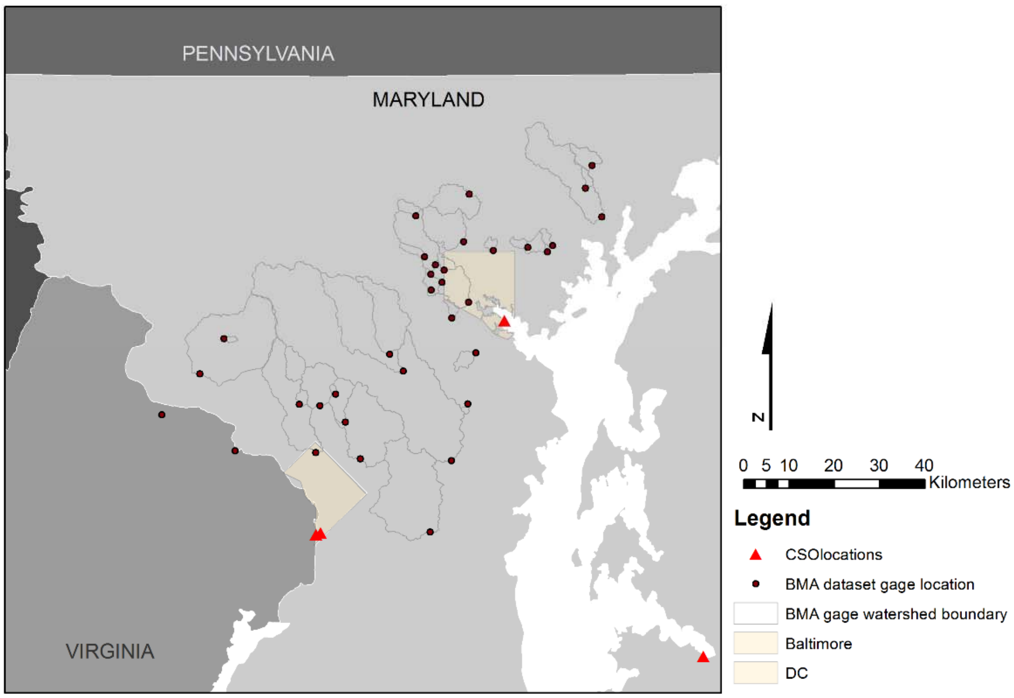

Figure 3.2. BMA dataset gauge locations and basin boundaries

After the time-series-averaged precipitation data was obtained for each watershed, the procedure used for pairing rainfall events with flow gauge readings was identical to that of the national dataset. Due to data limitations, only 34 watersheds over 30% developed were left for the study (**Figure 3.2**). The watersheds ranged from 31.86% developed to 96.87% developed. The average annual precipitation depth (from 1970-2000) ranged from 107.9 cm to 123.3 cm. The drainage areas ranged from 1.20 km^2 to 906.60 km^2. Some watersheds that were not included in the national-level dataset because of a lack of a proximate rain gauge station were included in the Baltimore Metropolitan Area dataset, for which the more accurate radar precipitation data was available. Combined sewer outfall proximity was calculated as for the national-level dataset. Using the same internet search method as was used for the national dataset, all counties for the BMA catchments were determined to have implemented detention, retention or infiltration-based stormwater management policies, therefore the effect of this development characteristic could not be estimated through regression and it was not included in the BMA analysis. Between the national and BMA datasets, there were 119 unique catchments included in the study.

Hydrograph Separation and Event Definition

I used the R package ‘EcoHydRology’ to separate the hydrographs into baseflow and quickflow components (Fuka *et al.*, 2014). By visual inspection of the hydrograph separation for a 12.7 mm (0.5 inches) rainfall event and a 38.1 mm rainfall event (1.5 inches) for a few representative watersheds, I determined that a filter parameter of 0.925 and three passes was appropriate to automate baseflow separation across the variation in my analysis catchments. Since some catchments exhibited very little response to rainfall, I defined the start and end of rainfall events from the continuous precipitation record. Events were defined as any length of time that preceded and followed by 96-hour periods of no rainfall in the precipitation record. The implicit assumption of the 96-hour dry period is that localized groundwater mounding or saturation that could contribute to VSA within a catchment would decrease in influence after that period. To capture the full quickflow component of the hydrograph in the flow record (especially in larger catchments), I added a buffer of 36 hours after the precipitation-defined end time of the event. Through separated hydrograph inspection, I confirmed that the 36- hour period was long enough to capture the quickflow response even from the larger catchments in the dataset. An example of the separation (described below) is shown in **Figure 3.3.** The time step for all hydrograph separation was 15 minutes. All flow data were available at least at this resolution. Flow data collected at a higher resolution time step were averaged to 15 minute intervals.

For each event, precipitation depths were summed and paired with cumulative quickflows over the defined event period and normalized by dividing by the catchment area. Thus, for each analysis catchment, a set of paired rainfall-runoff depths for each event was created. An identical process was carried out for the BMA dataset, except that the source of the precipitation data was basin-averaged, bias-corrected HYDRO-NEXRAD data.

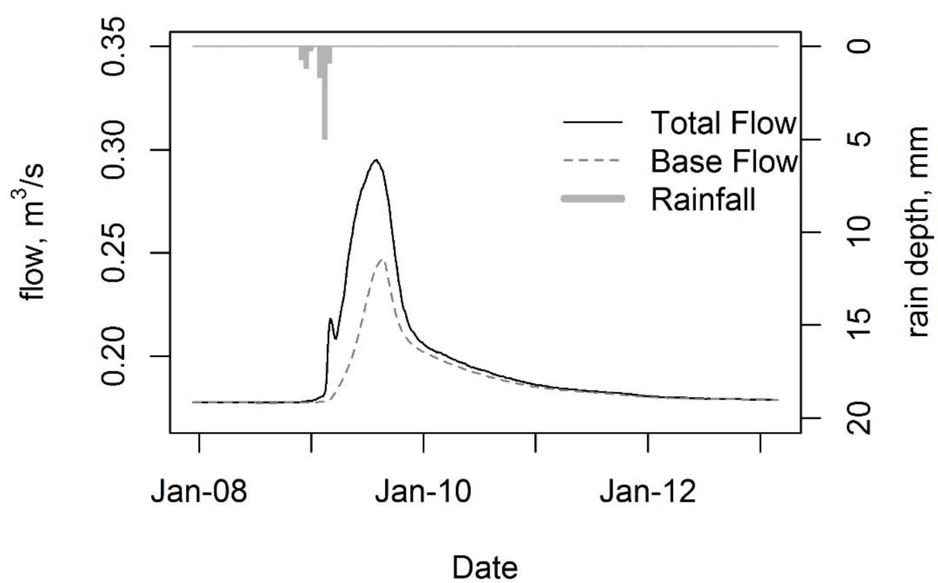

Figure 3.3. Example of hydrograph separation using R package 'EcoHydRology' for the watershed in our sample with the largest drainage area, Salado Creek in San Antonio, TX (drainage area = 505.8 km^2). The flow response to a 38.1 mm (1.5 inch) total rainfall depth is shown. The response returns to baseflow conditions within the 36-hour period.

ROBUST STATISTICAL DETECTION OF VSA

Classification of catchments as having dominant VSA processes was based on the statistical detection of nonlinearity in the rainfall-runoff response of the catchment. Statistical significance of nonlinearity was determined through the estimation of the linear model:

$$runoff_{ij} = \alpha_i + \beta_{1i} rain_{ij} + \beta_{2i} \exp rain_{ij} + u_{ij} \qquad [3.1]$$

where $rain_{ij}$ is the precipitation depth of each event j in the time period for catchment i and $runoff_{ij}$ is the runoff depth corresponding to precipitation event j. If the coefficient estimated for exp($rain_{ij}$) was statistically significant, this indicated evidence of nonlinearity in the rainfall-runoff relationship averaged over many events. In the detection of VSA processes, I expected this nonlinearity to be positive.

One problem with the above specification is that it suffers from heteroscedasticity, or non-constant variance in the residuals of the estimated equation. While heteroscedasticity does not bias the estimates of the coefficients in a linear regression, it does result in inefficient estimates of the standard errors of the coefficient estimates. In order to correct the effects of heteroscedasticity on standard error estimates of the coefficients, I log-transformed both the rainfall and runoff data to improve residual distribution. I used the R package 'sandwich' to estimate robust standard errors for the coefficients of the log transformed model [3.1] (Zeileis, 2004). I assigned catchments as VSA-dominant if $\beta_2$was significant at the α=0.05 level, and non-VSA dominant if β_2 was not significant at the α = 0.05 level. The result of this part of the analysis was an assigned binary hydrological response variable for each of the analysis watersheds: linear, corresponding to no evidence of VSA processes (Z_i = 0), or nonlinear, corresponding to evidence of VSA processes (Z_i = 1).

Seasonal effects have been shown to influence nonlinearity in event-based rainfall-runoff ratios (Smith *et al.*, 2005; Detty and McGuire, 2010; Meierdiercks *et al.*, 2010b). During the growing season, evapotranspiration reduces soil moisture, allowing catchments to recover volume more quickly between events. We would therefore expect dormant season subsurface conditions to stay wetter longer and to be more associated with a constant response. In order to gain more clarity on potential sources of variation in nonlinear rainfall-runoff ratios, I specified an additional model to test whether growing season rainfall events have a statistically different rainfall-runoff relationship than dormant season events. The dormant season was defined as the months from October – March and the growing season was defined as the months from April – September (Detty and McGuire, 2010).

The above-specified model [3.1] allowing for an additional effect of seasonality is shown in model [2]:

$$runoff_{ij} = \alpha_{1i} + \beta_{1i} rain_{ij} + \beta_{2i} \exp(rain_{ij}) +$$

$$\alpha_{2i} g_{ij} + \beta_{3i} rain_{ij} \times g_{ij} + \beta_{4i} \exp(rain_{ij}) \times g_{ij} + u_{ij} \qquad [3.2]$$

where g_{ij} is a dummy variable equal to one if event *j* occurred during the growing season and zero if event *j* occurred during the dormant season. If the regression [3.2] for catchment *i* results in significant coefficients α_{2i}, β_{3i}, or β_{4i}, this indicates that the rainfall-runoff ratio is statistically different during the growing season than during the dormant season. The model allowing for estimates effects for seasonality [3.2] was log-transformed in the same way the restricted model [3.1] was log-transformed.

The choice of the exponential form of the term capturing nonlinearity is contrasted to the "breakpoint" or threshold conceptualization of nonlinearity that has been applied in other studies (e.g., Loperfido *et al*. (2014)). The exponentiated form is preferred for its ability to better reflect incremental exceedance of area-based storage within the catchment and thus, incremental hydrologic connectivity of areas to the downstream streamflow response. The choice to discretize the detection of VSA-type response is limited because it does not capture variation in the magnitude of nonlinearity; however, the focus of this analysis was on explaining the VSA process, rather than on predicting runoff magnitudes from rainfall depths.

LOGISTIC REGRESSION OF VSA ON CATCHMENT CHARACTERISTICS

After obtaining the binary VSA (nonlinear) or non-VSA (linear) response classification for each watershed was obtained, logistic regression was used to test which explanatory variables (catchment characteristics) contributed to the probability of a catchment exhibiting a nonlinear response. The probability of VSA-type response is expressed as an inverse logistic function of catchment characteristics in [3.3]:

$$\Pr(Z_i = 1) = \mathrm{logit}^{-1}(\boldsymbol{M_i}\boldsymbol{\gamma_i}) \qquad [3.3]$$

where $\boldsymbol{M_i}$ is the vector of k characteristics for catchment i $(m_{1i}\ldots m_{ki})$, and $\boldsymbol{\gamma_i}$ is the vector of coefficients for the characteristics of catchment *i.* Of particular interest was estimating the effect of development and specifically impervious surface on the probability of a catchment exhibiting a VSA-type (nonlinear) response. Other variables tested as part of the vector **M** included: average slope, average annual precipitation, number of data observations, size of the drainage area, percent of various land use types, stream order, basin compactness (a measure of elongation), and region. In the final models, theoretically important variables and variables statistically significant at the α = 0.10, 0.05 and 0.01 levels were included.

To test my hypotheses, I fit [3.3] using two sets of models for each of the three datasets (national, BMA, and non-CSS only). The first set of models (Models 1A-1C, shown in **Table 3.2**) starts with percent undeveloped land as the sole predictor of VSA-type response (Model 1A), then sequentially adds geologic/morphologic controls as predictor variables in the model (Model 1B), followed by other development characteristic controls (Model 1C). The set of geologic/morphologic and meteorological controls in the models included average slope (%), average annual precipitation (cm/yr), and catchment area (km^2). Watersheds with lower average slopes are expected to exhibit more variability in the saturated zone and from subsurface throughflow, which result in a VSA response (Dunne *et al.*, 1975). Smaller basins are likely to exhibit flashier hydrological response, which may be associated with reduced VSA effects (Smith and Smith, 2015). The meteorological control included was the average total annual precipitation in the watershed. Higher annual precipitation is likely to be positively associated with humid climates that are likely more dominated by VSA processes than by Hortonian flow, all else being equal (Dunne *et al.*, 1975; Miles and Band, 2015). Other development characteristic controls included percent TIA, percent developed open space, distance to combined sewer outfall and a binary variable for decentralized stormwater management practices. Percent undeveloped land was calculated from the GAGES II database by subtracting low, medium, and high density development and developed open space percentages from 100%. Developed open space is a National Land Cover Dataset (NLCD) classification defined as the percent of the 30m x 30m grids within the watershed that is estimated to have less than 20% impervious cover. Typically, these areas include large-lot single-family housing units, parks, golf courses and landscaped vegetation in developed areas.

In the second set of models, I removed percent undeveloped land as a predictor variable and only include development-type variables (Models 2A-2C, shown in **Table 3.3**). Starting with percent impervious area along with the geologic/morphologic and meteorological controls (Model 2A), I add in other development-type variables, for percent developed open space (Model 2B), and distance to combined sewer outfall, and decentralized stormwater management practices (Model 2C). Estimating the effects of development-type variables separately from the percent undeveloped area variable allows us to test how different development types contribute to explaining the variation in VSA-type response and avoid multicollinearity of explanatory variables.

Goodness-of-fit for the logistic regressions was assessed using two methods: McFadden's pseudo R-squared and a percent-correctly-predicted pseudo R-squared where the cutoff point was defined as the mean of the dependent variable (Wooldridge, 2010). The likelihood ratio test was used to evaluate whether the inclusion of additional explanatory variables led to statistical improvement of the model's fit to the data.

RESULTS

Classification

The robust catchment classification methodology resulted in 69 out of 91 total national-level catchments (76%), 21 of 34 total BMA catchments (62%) and 44 out of 56 total non-

CSS watersheds (78%) being classified as having statistical evidence of VSA-processes. Among the national dataset basins, those classified as having nonlinear response had an average drainage area of 90.96 km^2, while those classified as having a linear response had an average drainage area of 66.5 km^2. T-test results showed that the difference in means was not statistically significant at the 0.05 level ($p = .246$, $n_1 = 69$, $n_2 = 22$). **Table 3.2** shows the estimated linear and nonlinear coefficients and significance according to the robust standard errors for the BMA watersheds (national dataset results are included as supplemental information). **Figure 3.3** illustrates the linear and nonlinear fits for several example watersheds. From these visual inspections of the fits to the data, I determined that the classifications based on the regression specifications and the robust standard error calculations for both the national (and non-CSS) dataset and the BMA dataset were satisfactory.

TABLE 3.2: Estimated linear and nonlinear coefficients and robust standard errors for Baltimore Metropolitan Area watersheds

Station ID	Name	Drainage area (km^2)	Percent Developed	Linear Coefficient			Non-linear Coefficient		
				Esti-mate	Robust Std err		Esti-mate	Robust Std err	
1581500	BYNUM RUN AT BEL AIR, MD	21.7	65.96	0.537	0.07	*	1.045	0.19	*
1581752	PLUMTREE RUN NEAR BEL AIR, MD	6.5	78.88	0.690	0.07	*	0.874	0.26	*
1581757	OTTER POINT CREEK NEAR EDGEWOOD, MD	139	32.08	0.463	0.05	*	1.208	0.18	*
1583600	BEAVERDAM RUN AT COCKEYSVILLE, MD	53.6	51.17	0.271	0.06	*	0.706	0.21	*
1585090	WHITEMARSH RUN NEAR FULLERTON, MD	6.9	87.64	0.791	0.09	*	0.825	0.29	*
1585100	WHITEMARSH RUN AT WHITE MARSH, MD	19.7	84.78	0.727	0.09	*	0.940	0.32	*
1585104	HONEYGO RUN NEAR WHITE MARSH, MD	6.1	68.19	0.623	0.10	*	0.988	0.30	*
1585200	WEST BRANCH HERRING RUN AT IDLEWYLDE, MD	6	86.64	0.817	0.08	*	0.304	0.27	
1589100	EAST BRANCH HERBERT RUN AT ARBUTUS, MD	6.4	91.3	0.930	0.14	*	0.030	0.58	
1589197	GWYNNS FALLS NEAR DELIGHT, MD	10.6	78.43	0.730	0.10	*	0.424	0.41	
1589290	SCOTTS LEVEL BRANCH AT ROCKDALE, MD	8.7	79.51	0.627	0.06	*	0.915	0.22	*
1589300	GWYNNS FALLS AT VILLA NOVA, MD	84.5	65.79	0.561	0.06	*	1.001	0.16	*
1589305	POWDER MILL RUN NEAR LOCHEARN, MD	9.2	89.08	0.848	0.07	*	0.428	0.24	*
1589312	DEAD RUN NEAR CATONSVILLE, MD	2	95.63	0.991	0.08	*	0.256	0.20	
1589317	TRIBUTARY TO DEAD RUN TRIBUTARY AT WOODLAWN, MD	1.2	96.87	1.000	0.08	*	0.302	0.20	
1589330	DEAD RUN AT FRANKLINTOWN, MD	14.2	95.2	0.969	0.09	*	0.502	0.25	*
1589352	GWYNNS FALLS AT WASHINGTON BLVD AT BALTIMORE, MD	159.1	75.72	0.624	0.05	*	0.720	0.18	*
1589440	JONES FALLS AT SORRENTO, MD	65.1	33.9	0.403	0.05	*	1.010	0.22	*

1589500	SAWMILL CREEK AT GLEN BURNIE, MD	12.6	66.55	0.446	0.06	*	0.563	0.24	*
1589795	SOUTH FORK JABEZ BRANCH AT MILLERSVILLE, MD	2.5	35.6	0.213	0.08	*	1.769	0.27	*
1593500	LITTLE PATUXENT RIVER AT GUILFORD, MD	98	58.66	0.445	0.04	*	1.010	0.22	*
1594000	LITTLE PATUXENT RIVER AT SAVAGE, MD	254.4	37.02	0.468	0.07	*	0.589	0.26	*
1594440	PATUXENT RIVER NEAR BOWIE, MD	906.6	31.86	0.387	0.08	*	0.541	0.32	*
1594526	WESTERN BRANCH AT UPPER MARLBORO, MD	233.6	50.38	0.610	0.05	*	0.661	0.18	*
1644280	BROAD RUN NEAR LEESBURG, VA	196.9	56.03	0.299	0.11	*	0.520	0.61	
1644375	LITTLE SENECA CREEK TRIBUTARY NEAR GERMANTOWN, MD	3.3	82.65	0.625	0.09	*	0.527	0.38	
1645000	SENECA CREEK AT DAWSONVILLE, MD	262.4	36.92	0.296	0.07	*	-0.054	0.15	
1646000	DIFFICULT RUN NEAR GREAT FALLS, VA	149.9	50.53	0.623	0.09	*	0.280	0.40	
1647850	TURKEY BRANCH NEAR ROCKVILLE, MD	7	88.48	0.968	0.13	*	-0.114	0.54	
1648000	ROCK CREEK AT SHERRILL DRIVE WASHINGTON, DC	136.8	70.99	0.715	0.11	*	-0.415	0.44	
1649150	PAINT BRANCH TRIBUTARY NEAR COLESVILLE, MD	2.7	39.35	0.456	0.08	*	1.115	0.30	*
1649190	PAINT BRANCH NEAR COLLEGE PARK, MARYLAND	34	57.34	0.483	0.09	*	0.351	0.36	
1649500	NORTH EAST BRANCH ANACOSTIA RIVER AT RIVERDALE, MD	188.1	62.92	0.567	0.08	*	0.644	0.28	*
1650500	NW BRANCH ANACOSTIA RIVER NEAR COLESVILLE, MD	54.8	48.29	0.665	0.11	*	-0.010	0.46	

* indicates coefficient estimate is significant at the alpha = 0.05 level.

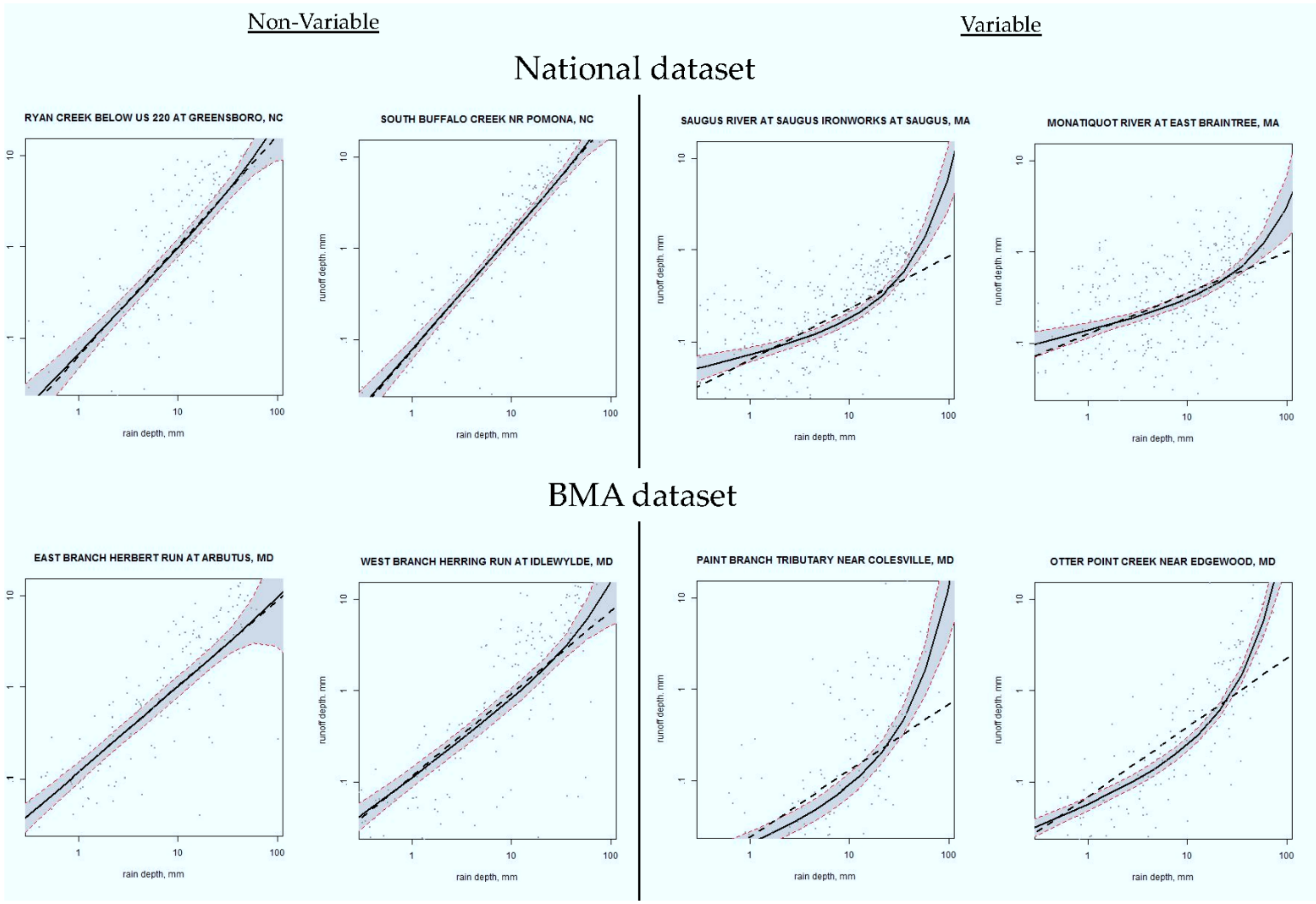

FIGURE 3.4: Example plots of linear and nonlinear relationships between rainfall and runoff (log transformed). Gray areas represent 90% confidence interval of model fit with both linear and nonlinear terms included, using robust standard estimates.

The solid line is the predicted relationship with both linear and nonlinear terms included. The dashed line is the predicted relationship with only the linear term included

In order to determine whether the addition of the dummy variable for growing season and its interaction with the linear and nonlinear components of the regression significantly improved the fit of the model, I employed a heteroscedastic standard errors-robust F-test comparing the fits of the nested models [3.1] and [3.2]. In the majority of the catchments in both the national and BMA datasets, there was no significant improvement in model fit by including the dummy variable for growing season (57/91 catchments in the national dataset and 26/34 catchments in the BMA dataset exhibited no significant differences in fit compared to the restricted model [3.1], where the values of α_{2i}, β_{3i}, and $\beta_{4i}$are all constrained to the value 0). Of the catchments that did exhibit improvement by incorporating seasonal differences, many estimated individual effects that were insignificant at the 0.05 level for all three additional seasonal terms (9/34 for the national dataset and 2/8 for the BMA dataset).

Among the seasonal models [3.2] that did exhibit some improvement over the restricted models [3.1], the interpretation of significantly estimated regression coefficients of may provide some additional insight into the dynamics of urban VSA runoff behavior. **Figure 3.5** shows the classifications of each basin included in this study, first by whether the fit of the model was improved with the inclusion season-specific variables, then by the year-round classification as exhibiting evidence of VSA-behavior, and lastly, by significance and signs of estimated season-specific effects. **Figure 3.5** shows that among those catchments for which the addition of the seasonal variables significantly improved fit, 9/20 of the national dataset and 2/8 of the BMA dataset had insignificant effects for all three variables. For both datasets however, the next frequent classification among those with improved models was for non-VSA basins with significant nonlinear behavior during the growing season. This coefficient was estimated as positive in 4/5 national catchments in this category and 2/2 of BMA catchments in this category. Both these findings are in agreement with the present understanding of VSA runoff generation, which suggests that variable source area dynamics would be more pronounced during the growing season, when evapotranspiration allows basins to recover storage volume more quickly (Detty and McGuire, 2010).

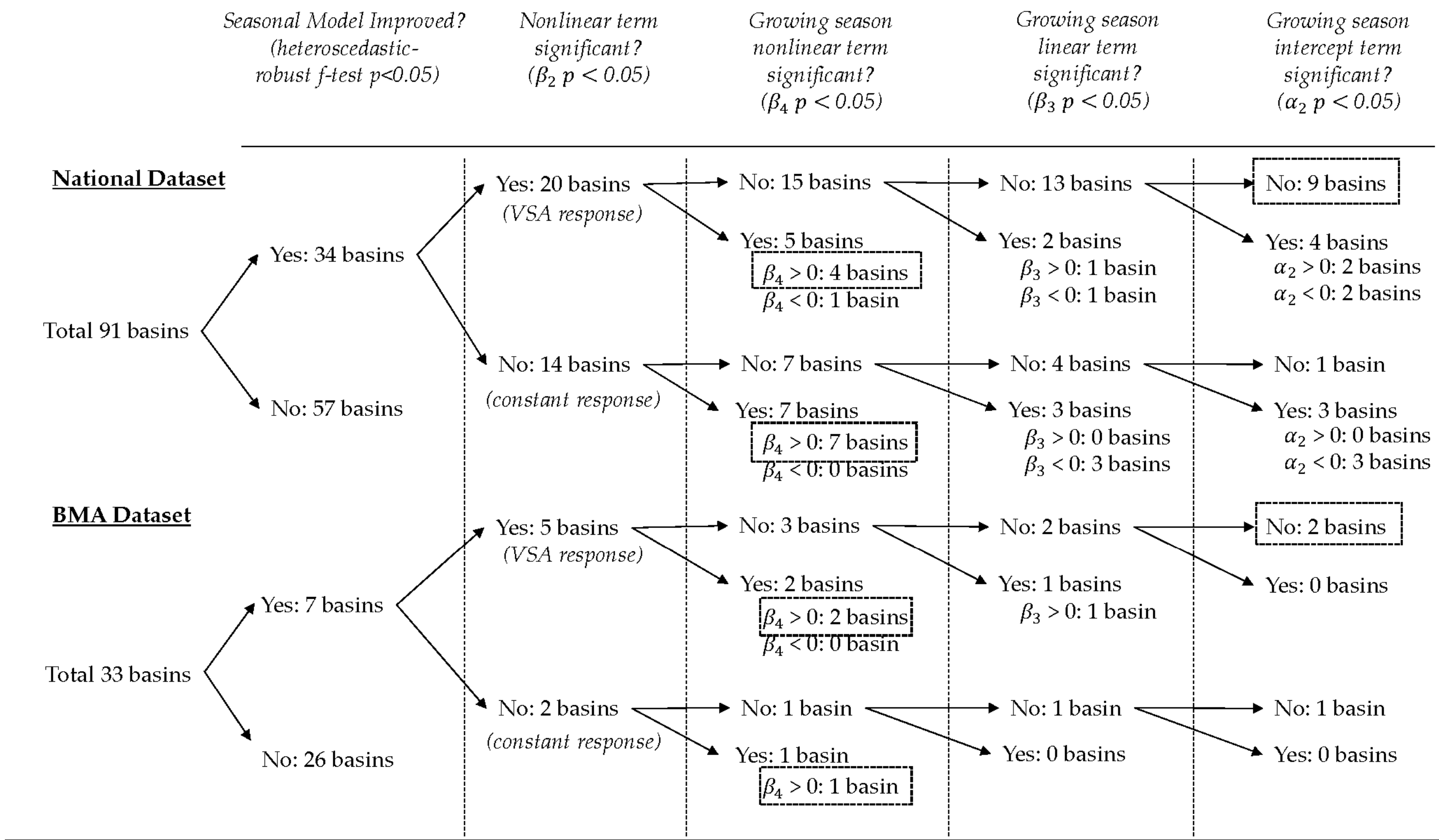

FIGURE 3.5 Classification of all analysis basins included in this study based on model improvement with inclusion of seasonal controls, significance of nonlinear term (evidence of VSA behavior), and significance and sign of estimated coefficients

associated with effect of rainfall-runoff ratio relationship during the growing season (April – Sep). Of catchments whose models were improved by controlling for seasonality and had significant individual coefficients, the highest frequency that appeared were for VSA catchments with positive coefficients for the nonlinear seasonal term. This is in agreement with previous theory and findings that VSA response should be more pronounced during the growing season.

Predictors of Urban VSA

Table 3.3 shows the results of the regressions that include the percent of the watershed that is undeveloped as a predictor of the VSA-classification. For the national dataset, percent undeveloped area alone was a significant predictor of a VSA-type response. A 1% increase in the percent undeveloped land within a watershed was associated with a 3.5% increase in the odds of a watershed exhibiting VSA-type response. For all three datasets, including morphological and meteorological controls in Model 1B led to significant improvement over Model 1A. A likelihood ratio test between Models 1B and 1A yielded p-values of 0.035, 0.00087, and 0.0084 for the national dataset, BMA dataset and CSS dataset, respectively. Based on Model 1B, the effect of a 1% increase in undeveloped land was associated with between 5.5% and 10.8% increase in the odds of the watershed exhibiting evidence of a VSA-type response, controlling for slope, precipitation, and catchment area.

Table 3.3: Results of logistic regression of percent undeveloped land and other controls on probability of VSA-type response

	MODEL 1A: Undeveloped Land				MODEL1B: Undeveloped Land + Morphologic and Meteorological Controls					MODEL1C: Undeveloped Land + Development Characteristics + Morph/Met Controls				
Panel A: National Dataset (n = 91)														
	Estimate	Effect on Odds (%)	t-statistic [a]		Estimate	Effect on Odds (%)	t-statistic		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF
Undeveloped Land (%)	0.034	3.476	1.327	.	0.053	5.488	2.392	*	1.324	0.066	6.842	1.233		6.981
Total Impervious Area (%)										0.012	1.249	0.133		14.579
Developed Open Space (%)										-0.032	-3.154	-0.502		6.655
Distance to CSO (m)										0.000	0.000	0.535		1.965
Ret/Det SW Infrastructure (binary)										0.301	35.081	0.459		1.483
Average Slope (%)					-0.441	-35.682	-2.225	*	1.370	-0.298	-25.763	-1.332		1.670
Average Annual Precipitation (cm/yr)					0.038	3.892	1.964	*	1.159	0.036	3.692	1.456		1.694
Catchment Area (km^2)					0.002	0.152	0.448		1.143	0.000	0.015	0.036		1.547
Intercept	0.516	67.566	0.185		-3.160	-96	-1.491			-3.270	-96	-0.694		
McFadden's R^2	0.038				0.124					0.143				
Count-based R^2 (above mean)	0.560				0.670					0.692				

Panel B: BMA Dataset (n = 34) [(b)]

	Estimate	Effect on Odds (%)	t-statistic	Estimate	Effect on Odds (%)	t-statistic		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF
Undeveloped Land (%)	0.027	2.747	1.462	0.102	10.760	2.157	*	3.430	0.328	38.814	1.372	*	48.338
Total Impervious Area (%)									-0.132	-12.367	-0.509		25.004
Developed Open Space (%)									-0.452	-36.388	-1.465		15.031
Distance to CSO (m)									0.000	-0.048	-1.656	.	9.857
Average Slope (%)				-1.820	-83.793	-2.012	*	3.263	-3.394	-96.642	-1.689	*	6.552
Average Annual Precipitation (cm/yr)				0.770	115.977	2.640	**	3.644	1.498	347.274	2.235	**	11.126
Catchment Area (km^2)				0.004	0.380	0.536		1.639	0.000	0.007	0.004		2.905
Intercept	-0.415	-33.942	-0.601	-85.310	-100	-2.648	**		-144.114	-100	-2.222		
McFadden's R^2	0.051			0.417					0.672				
Count-based R^2 (above mean)	0.618			0.853					0.941				

Panel C: non-CSS Dataset (n = 56) [(c)]

	Estimate	Effect on Odds (%)	t-statistic	Estimate	Effect on Odds (%)	t-statistic		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF
Undeveloped Land (%)	0.036	3.668	1.444	0.087	9.039	2.186	*	1.980	0.130	13.880	1.197		11.825
Total Impervious Area (%)									0.075	7.773	0.411		20.343
Developed Open Space (%)									-0.046	-4.475	-0.434		6.890
Average Slope (%)				-1.207	-70.091	-2.756	***	1.860	-0.920	-60.151	-1.793	.	1.805
Average Annual Precipitation (cm/yr)				-0.040	-3.937	-1.074		1.284	-0.030	-2.985	-0.744		1.481
Catchment Area (km^2)				-0.002	-0.191	-0.373		1.460	-0.004	-0.371	-0.697		1.721
Intercept	0.709	103.196	1.459	7.285	145732	1.539			3.932	5003	0.397		
McFadden's R^2	0.040			0.241					0.325				
Count-based R^2 (above mean)	0.536			0.768					0.821				

(a) . Significance at the 0.10 level ; * Significance at the 0.05 level; ** Significance at the 0.01 level

(b) Retention/Detention stormwater infrastructure excluded because all BMA watersheds located in counties with detention, retention or infiltration-based infrastructure

(c) Distance to CSO and Ret/Det stormwater infrastructure effects could not be estimated due to complete separation in the data

Adding in controls for development types sequentially did not further statistically improve the model fits for the national or BMA datasets but some improvement was shown with the non-CSS dataset. One model (not shown in **Table 3.3**) estimated with the non-CSS dataset which included percent developed open space, percent undeveloped land and the morphological and meteorological controls (but excluding percent impervious area), did estimate statistically significant results for both undeveloped land and developed open space and this model was shown to be a statistical improvement over Model 1B (p = 0.03053). The effect of undeveloped land was similar to that estimated in Model 1B (9.32%), but the effect of developed open space was estimated to be -8.232% (p = 0.0463). In contrast, the effect of impervious area is not significant at the $\alpha = 0.05$ level when included with undeveloped area with any of the datasets. This suggests that developed open space functions more similarly to what we would expect from impervious area, and that this effect is most prevalent watersheds that do not have CSS.

Model 1C, which also includes percent impervious area as an explanatory variable, showed slightly significant (p = 0.09) improvement over Model 1B for the non-CSS dataset, but none of the development variable coefficients were estimated to be statistically significant from zero. Model 1C exhibited the problem of rather high variance inflation factors for multiple variables for all three datasets. High VIFs are an indication of multicollinearity between the explanatory variables. Generally, VIF values >10 result in unreliable estimates (Kutner *et al.*, 2004). When percent TIA was removed from Model 1C for the non-CSS dataset, all VIFs fell below 2, suggesting that the source of collinearity was between percent undeveloped and TIA and percent developed open space and TIA, and not between percent developed open space and percent undeveloped.

A second set of models excluded the percent undeveloped variable to avoid multicollinearity and focus on the effects of percent impervious area, which is commonly identified as the strongest factor in decreased catchment storage and flashier hydrologic response (**Table 3.4**). The effect of impervious surface area was not found to be a significant predictor of a VSA-type response until other contextual factors were controlled for. Adding morphologic and meteorological controls (Model 2A), a significant effect was only estimated with the BMA dataset. A 1% increase in the percent impervious area was associated with an 11.1% decrease in the odds of a VSA-type response. TIA only became statistically significant for all three dataset after also controlling for percent developed open space (Model 2B) and a likelihood ratio test also indicates that the model improvement over 2A is statistically significant (p-values for the improvement of Model 2B over Model 2A were 0.01276, 0.08941, and 0.001745 for the national, BMA, and non-CSS datasets, respectively). These models estimated between an 8.0% and 17.9% decrease in the odds of VSA-type response associated with a 1% increase in TIA.

Table 3.4: Results of logistic regression of development types and other controls on probability of VSA-type response

Panel A: National Dataset (n = 91)	MODEL 2A: TIA					MODEL2B: TIA + Open Space					MODEL2C: TIA + Open Space + Other Development Characteristics				
	Estimate	Effect on Odds (%)	t-statistic [(a)]		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF
Total Impervious Area (%)	-0.023	-2.235	-0.861		1.400	-0.083	-7.981	-2.157	*	2.724	-0.092	-8.758	-2.275	*	2.932
Developed Open Space (%)						-0.089	-8.554	-2.364	*	2.433	-0.095	-9.095	-2.449	*	2.591
Distance to CSO (m)											0.000	0.000	0.789		1.873
Ret/Det SW Infrastructure (binary)											0.120	12.776	0.190		1.411
Average Slope (%)	-0.327	-27.879	-1.613		1.509	-0.348	-29.363	-1.669	.	1.517	-0.289	-25.068	-1.304		1.656
Average Annual Precipitation (cm/yr)	0.036	3.646	1.919	.	1.177	0.052	5.319	2.465	*	1.378	0.048	4.906	2.111	*	1.457
Catchment Area (km^2)	0.003	0.350	0.290		1.066	0.002	0.222	0.668		1.094	0.001	0.055	0.134		1.529
Intercept	-1.621	-80.234	-0.781			0.881	141.303	0.362			1.472	335.976	0.547		
McFadden's R^2	0.066					0.128					0.553				
Count-based R^2 (above mean)	0.626					0.648					0.703				

Panel B: BMA Dataset (n = 34) [(b)]

	Estimate	Effect on Odds (%)	t-statistic		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF
Total Impervious Area (%)	-0.117	-11.081	-2.052	*		-0.197	-17.855	-2.154	*	4.617	-0.438	-35.489	-2.160	*	14.001
Developed Open Space (%)						-0.163	-15.022	-1.502		2.695	-0.441	-35.647	-1.818	.	8.968
Distance to CSO (m)											0.000	-0.029	-1.932	.	4.348
Average Slope (%)	-1.456	-76.679	-1.938	.		-1.711	-81.932	-1.965	*	2.913	-2.060	-87.254	-1.938	.	2.560
Average Annual Precipitation (cm/yr)	0.616	85.128	2.608	**		0.769	116	2.743	**	3.192	1.040	183	2.534	*	5.242
Catchment Area (km^2)	0.007	0.663	1.021			0.002	0.152	0.208		1.882	0.003	0.281	0.218		2.343
Intercept	-63.220	-100.000	-2.551	*		-73.528	-100	-2.682	**		-83.951	-100	-2.448	*	
McFadden's R^2	0.358					0.421					0.614				
Count-based R^2 (above mean)	0.794					0.824					0.853				

Panel C: non-CSS Dataset (n = 56) [(c)]

	Estimate	Effect on Odds (%)	t-statistic		VIF	Estimate	Effect on Odds (%)	t-statistic		VIF
Total Impervious Area (%)	-0.013	-1.284	-0.321		1.450	-0.132	-12.322	-1.968	*	3.058
Developed Open Space (%)						-0.156	-14.477	-2.700	**	2.220
Average Slope (%)	-0.762	-53.331	-2.037	*	1.450	-1.037	-64.554	-2.117	*	1.856

Average Annual Precipitation (cm/yr)	-0.017	-1.673	-0.524	1.062	-0.011	-1.062	-0.290		1.203
Catchment Area (km²)	0.004	0.406	0.831	1.073	-0.001	-0.103	-0.221		1.313
Intercept	5.014	14952	1.114		13.245	565465 40	2.001	*	
McFadden's R^2	0.131			0.299					
Count-based R^2 (above mean)	0.696			0.821					

(a) . Significance at the 0.10 level ; * Significance at the 0.05 level; ** Significance at the 0.01 level

(b) Retention/Detention stormwater infrastructure excluded because all BMA watersheds located in counties with detention, retention or infiltration-based infrastructure

(c) Distance to CSO and Ret/Det stormwater infrastructure effects could not be estimated due to complete separation in the data

The effect of developed open space was nearly equal in magnitude to that of TIA. A 1% increase in developed open space was associated with between 8.6% and 15.2% decrease in the odds of a VSA-type response. Adding variables representing type of development, such as distance to combined sewer outfall and presence of a retention, detention or infiltration-based stormwater management program (Model 2C), neither significantly improved model fit nor resulted in additional significant estimated effects (likelihood ratio test p values for improvement of Model 2C over 2B were 0.553 and 0.308 for the national and BMA datasets, respectively). Model 2C for the national dataset had acceptable VIF values, and controlling for the distance to the nearest combined sewer outfall and presence of distributed stormwater infrastructure resulted in little change to the estimated effects of TIA and developed open space, demonstrating stability of the model. The two models that showed statistically significant improvements—Models 1B and 2B—had similar goodness-of-fit measures and estimated effects of significant controls, further increasing confidence that the results were not spurious.

DISCUSSION

Effect of undeveloped land compared to land development variables in explaining VSA response

The results from models that included undeveloped land as an independent variable show that in general, development type variables add little compared to the explanatory power of undeveloped land for predicting VSA response. This is especially true when morphologic and meteorological controls are included. When no additional controls are included in the regressions, the effect of undeveloped land is marginally significant, while that of TIA is not significant. Only when controls for watershed morphologic and meteorological conditions does TIA become a stable predictor of VSA-response. This result is important considering the attention that impervious area as a singular metric has been given over the years, especially for land use planning purposes. The conditional significance of impervious area highlights the need to incorporate contextualizing factors into the understanding of catchment-scale hydrological response.

Effect of open space in urban areas on VSA response

As expected, the effect of TIA on VSA-response is negative: a 1% increase in TIA within the watershed is associated with between 8.0% and 17.9% decrease in the odds of detection of a VSA-type response, controlling for other factors. Less expected is that developed open area (low density development) also has a negative effect on VSA-type response almost equal in magnitude to TIA. This suggests that on average, developed pervious area is also associated with Hortonian-flow dominated responses compared to undeveloped areas, a result that has also been confirmed by others (Smith *et al.*, 2015). For land-use planners, this means it is not enough to limit imperviousness of new development. In order to preserve VSA-type response, it is necessary to limit even low-density development. TIA is highly correlated with overall development levels (Pearson's rho = 0.78, 0.80, and 0.91 for the national, BMA and non-CSS datasets, respectively), which explains why this particular metric may have been useful for land use planners in the past. Developed open space, which was shown in this study to add significantly to the explanatory power of TIA, is not correlated with overall development (Pearson's rho = -0.13, -0.09, 0.15 for the national, BMA and non-CSS datasets, respectively). This weak correlation, along with the relative invisibility of runoff generation on pervious surfaces compared to impervious surfaces, may explain why the effect of developed open space has been overlooked.

There are several possible explanations for why developed open space has a negative effect on VSA-type response. Developed open space in the NLCD is defined as development that is less than 20% impervious, so these areas could still contain roads and drainage infrastructure that increase hydraulic connectivity. Urban pervious surfaces could have very little storage due to compaction and localized subsurface saturation due to lawn watering and leakage and therefore lead to saturation overflow conditions even during very small events (Lerner, 2002; Bhaskar and Welty, 2012; Smith and Smith, 2015). Although this process is physically more similar to Dunne's VSA concept of saturation overland flow, if storage is minimal, the hydrological response at this level of analysis is indistinguishable from Hortonian overland flow.

Effects of stormwater management infrastructure on VSA response

In the national dataset, no coefficients estimated for stormwater management control variables had statistically significant effects, and distance to CSO in the BMA dataset had only a marginally significant negative effect on VSA response. Many urban areas in the Northeast and Midwest US are served by combined sewer systems that collect wastewater and stormwater runoff within the same system. During small rain events, these collection systems do not discharge directly to streams, but direct all flows to the wastewater treatment plant, after which, runoff generated in one catchment may be discharged in another. The presence of this kind of infrastructure might suppress the detection of runoff response in highly urbanized areas, mitigating some of the negative effect of high levels of impervious surface in urbanized areas and resulting in decreased (less negative) effects on the probability of VSA compared to suburban areas. The more negative effect of developed open space estimated from the non-CSS dataset offers some supporting evidence that this is true: among watersheds in which runoff is not intercepted by wastewater collection and treatment systems, there is more of a Hortonian-type hydrological response. The data used in this analysis and the formulation of urban VSA include both runoff generation processes and the effects of intermediary structures that could confound the detection of a non-constant rainfall-runoff relationship (**Table 3.1**). However, previously demonstrated empirical evidence that variable source dynamics are more pronounced during summer months were also supported. It should be noted however, that the implications of a "VSA" type response that results from runoff being sent to a wastewater treatment plant during small storms but discharging runoff during large events has very different implications for watershed management than more natural VSA runoff production processes. Estimating the effect of retention, detention and infiltration-based stormwater management practices from the presence of guidelines including these practices does not necessarily reflect extent of implementation. However, previous research has shown that despite being constructed with modern detention and retention ponds, developed basins in Maryland still functioned more similarly to basins without such infrastructure than to an undeveloped, forested basin (Meierdiercks *et al.*, 2010b).

There are limitations of the data used in this analysis. While the GAGES II dataset is valuable because it allows for a cross-sectional analysis of many watersheds across the US, the resolution of land cover and precipitation data is too low to distinguish among specific physical processes of localized runoff generation. The particular processes and pathways within urbanized catchments ideally should be assessed in the field, and therefore, the conclusions of this study should be understood as the 'average' effects of the covariates included in the regressions, as measured at the stream gauge. It could be that issues of resolution among the urbanized catchments studied may mask the specific connectivity conditions of 'developed open space.'

CONCLUSIONS

This study confirms the need to move away from impervious surface as a singular metric for hydrological response, but has particular implications for land use planners and watershed managers. Previous emphasis on limiting imperviousness of new development suggests that low density, suburban development results in less disruption of hydrological response because of the presence of open space to mitigate flows. This study provides evidence that developed open space functions more similarly to impervious area than it does to natural areas, and shows that there is no evidence that developed open space promotes VSA dynamics. This finding may provide watershed managers and land use planners with additional rationale to promote higher density urban development or redevelopment and preserve naturalized areas rather than develop at low densities with more developed open space. It also implies that bulk lot coverage or zoning regulations that limit imperviousness but do not specifically address preservation of naturalized vegetation or native, undisturbed soils should be reexamined.

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CHAPTER 4: COUPLED SURFACE – SUBSURFACE ECOHYDROLOGIC MODELING IN AN URBAN SEWERSHED: APPLICATION OF THE PARFLOW MODEL

INTRODUCTION AND BACKGROUND

To date, hydrological modeling of urbanized watersheds has focused primarily on land cover and surface type. Impervious surface area, has emerged has emerged as the dominant explanation for reduction of subsurface storage in urbanized watersheds (Schueler, 1994; Arnold and Gibbons, 1996; Moglen and Kim, 2007). However, as shown in the previous chapter "Beyond Imperviousness: Hydrologic Response at the Regional Watershed Scale" and an increasing number of numerical and empirical studies of urbanized catchments, impervious surface area may not be the dominant explanation for changes in the urban hydrological cycle (Bhaskar *et al.*, 2015; Smith *et al.*, 2015; Lim, 2016). In these studies, subsurface dynamics, inter-event capacity recovery through evapotranspiration from vegetation and potential interactions between overland flow and the differential contraction of saturated areas, and lower than expected porosity and hydraulic conductivity of compacted urban soils are offered as possible explanations for changes in the hydrological cycle associated with urbanization.

Empirical monitoring results measuring effectiveness of green infrastructure

Extensive monitoring has shown that GI is effective at the site scale in reducing peak flows and runoff volumes and increasing water quality from rainfall events (Davis, 2007, 2008; Emerson and Traver, 2008; Li *et al.*, 2009; Driscoll *et al.*, 2015; Page *et al.*, 2015). At the catchment-scale however, limited implementation of GI means that there are very few empirical studies comparing expected performance of GI to actual performance. In an

EPA-led experimental program, researchers documented measurable and statistically significant weakened correlation of event-based rainfall depths and measured stream gauge flows (indicating measurable effectiveness of GI), in a suburban watershed in Ohio (Shuster and Rhea, 2013). Loperfido *et. al.*(2014) empirically studied the rainfall-runoff response in four catchments in the Chesapeake Bay area for a year and a half, and concluded that distributed BMPs resulted in higher baseflows, higher minimum precipitation thresholds for stream response, better maximum discharge controls for small events and reduced runoff volumes for the 1000-year event. Both of these studies took place in regions with significant new development, and not in existing urban areas that were retrofitted with GI.

The need to account for surface-subsurface interactions in GI modeling

Previous research suggests that the interactions or feedbacks between surface and subsurface dynamics may have significant contributions to the local water balance and hydrology in urban environments. The concept of Urban Variable Source Area (UVSA) is an adaptation of Dunne's Variable Source Area (VSA) (See previous chapter), which states that heterogeneity of infiltration rates within a watershed has not only to do with the heterogeneity of soils; it is also dynamically related to the behavior of water over the topography of the landscape and in heterogeneous interactions with subsurface (shallow groundwater) capacity of soil. For example, "sag points" in the topography require longer inter-event dry periods to recover their full capacities than upslope locations. Thus, infiltration capacity is also determined by antecedent wetting conditions (Dunne *et al.*, 1975).

Figure 4.1 shows a conceptualization of how lateral subsurface and subsurface-surface interactions could result in variability of effectiveness of run-off interception areas depending on differential capacity recovery between events. Infiltration to the subsurface can result in temporary saturation of low lying areas. When precipitation falls on saturated low lying areas, overland flow is produced from areas that would not contribute to overland flow had they not been saturated, producing a "variable source area."

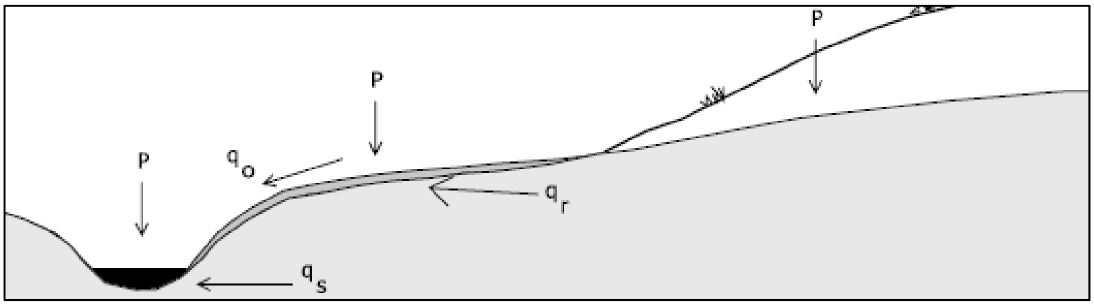


Figure 4.1. Example of fluxes influencing variable source area dynamics. *p* denotes precipitation, q_o denotes overland flow, q_r denotes return flow, and q_s denotes subsurface flow contributing to streamflow response. Source: Beven, 2012

UVSA (**Table 3.1**) acknowledges that run-on infiltration-based best management practices (BMPs) placed at different spatial locations within the sub-catchment could recover their infiltration capacities differently due to groundwater saturation, especially at sag points (Miles and Band, 2015). Imported water from leaking underground pipes and septic tanks may also be a substantial source of groundwater recharge and soil saturation in urban areas (Lerner, 2002; Meierdiercks *et al.*, 2010; Price, 2011). While many studies have focused on the effect of the easily-observable impervious surface on hydrological change, its effect on subsurface storage may not be so straightforward, as development is highly associated with imported water (leakages into the subsurface) and reduced vegetation (less evapotranspiration), and forced infiltration of stormwater runoff, which could actually result in increased subsurface storage (Ku *et al.*, 1992; Gobel *et al.*, 2004). The presence of drainage infrastructure has been shown to have different effects on UVSA depending on the size of the storm. During small storm events, drainage infrastructure results in higher connectivity and larger peak flows, but during large events, the presence of drainage infrastructure has been shown to reduce recharge to downslope areas, which then produce less runoff (Tague and Pohl-Costello, 2008). Several other studies have showed specifically that infiltration-based BMPs result in groundwater mounding, mounding is more severe when BMPs are spatially clustered together, and can exceed pre-development groundwater recharge (Gobel *et al.*, 2004; Endreny and Collins, 2009; Machusick, 2009; Maimone *et al.*, 2011).

While the above studies suggest that UVSA is likely to influence spatial location of infiltration within the watershed, few studies have addressed how lateral interactions and groundwater table feedbacks may influence hydrological effectiveness of widespread, infiltration-based GI at the catchment scale. Miles (2014) completed research on low to medium density infiltration-based GI using an eco-hydrology model that incorporated UVSA. The research showed that GI location (near stream or far from stream) did not significantly influence hydrological effectiveness. However, that non-finding may have been due to low overall levels of impervious area disconnection. In addition, that study did not include a model with overland flow routing that is associated with high levels of impervious area.

Whereas hydrologic processes are inherently three-dimensional, many modeling approaches average over one dimension to reduce model complexity, depending on the process of interest. Models focusing on surface processes often average over the vertical, whereas models focusing on infiltration processes focus on a vertical cross-section, implying a lateral average. Some hybrid models link these two approaches together to create a pseudo 3-d model. One study linked a natural distributed hydrological model with a lumped urban stormwater model to include solutions to overland flow routing likely to be associated with higher levels of imperviousness. This study confirmed that there were significant interactions between surface runoff generation and groundwater, with up to 24% of total discharge from the urban runoff network originating from groundwater (Kidmose *et al.*, 2015). Coupled models have been popular to deal with the vertical processes of evapotranspiration, infiltration, gravitational drainage and vertical soil moisture separately from lateral routing solutions (Bouilloud *et al.*, 2010). These coupled models have been adapted for suburban catchments, with very low infiltration rates specified for impervious surfaces and runoff drained through sewer networks (Furusho *et al.*, 2013). Overall the adaptation was shown to perform satisfactorily, although it tended to underestimate total discharge during dry periods because of unrealistic deep drainage assumptions, and overestimate total discharge during wet periods because runoff from impervious surfaces was overestimated (Furusho *et al.*, 2013).

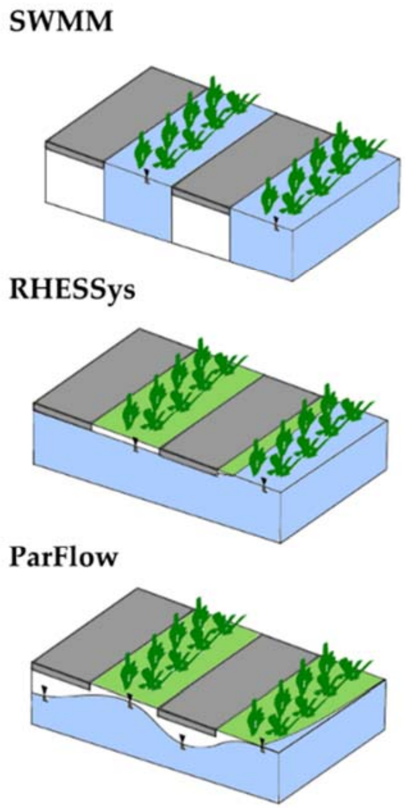
The majority of what we know about infiltration-based stormwater management at the catchment scale comes from hydrological modeling studies. These studies use our physical knowledge about hydrology to predict hydrological response to GI through mathematical expressions. All types of hydrological modeling can be characterized as belonging to one of three broad approaches: lumped, semi-lumped, and distributed. Lumped models treat the catchment as a single unit of analysis with averaged state parameters (such as TR-55 and the SCS Curve Number method) (USDA, 1986). Semi-lumped models break down the catchment area into sub-catchments with averaged state parameters. Distributed models discretize the entire catchment into grids and solve state variables for each grid pixel. Discretizing the catchment area allows the model to make predictions that are more finely distributed over space. Distributed models are also sometimes called “process-based” or “physics-based” models, since they are built on known physics-based relationships (Beven, 2012).

The majority of urban hydrological modeling belong to the lumped, or semi-lumped parameter approach, and many studies have demonstrated the effectiveness of GI at the catchment scale using these approaches (Gilroy and McCuen, 2009; Ahiablame *et al.*, 2013; Burszta-Adamiak and Mrowiec, 2013; Lee *et al.*, 2013; Qin *et al.*, 2013; Palla and Gnecco, 2015). While most lumped parameter approaches are still based on empirically-observed relationships and are easier to parameterize and not as computationally intensive as distributed models, their structure does not allow for the possibility of interactions or feedbacks that are distributed in space within the catchment or sub-catchment. Their lumped structure also makes it impossible to distinguish between distinct processes within the catchment, especially complex interactions in the subsurface and between subsurface and surface processes such as overland flow, interflow, evapotranspiration, and infiltration (Bhaskar *et al.*, 2015).

What remains unknown is how detailed, vertical water and energy fluxes such as those represented in eco-hydrological models or soil-vegetation-air transfer (SVAT) models might be incorporated into higher-intensity urban areas. These interactions are likely to be important because infiltration-based BMPs recover their volumes through evapotranspiration and because they all depend on availability of storage capacity in soils in order to work as expected. In medium-density urban areas, the spatial configuration of infiltration-based BMPs may make measurable differences in flows measured in the drainage system and to the overall local water balance. But previous models have not accounted for an adequate representation of both surface and subsurface interactions that are likely to be more important as urban catchments include more opportunities for infiltration.

Comparisons of common hydrological models

Figure 4.2 shows how three hydrological models treat surface-subsurface interactions. In the widely-used SWMM model (distributed by the EPA), a watershed can be divided into smaller subcatchment areas to make it more spatially distributed. Since within each subcatchment state parameters are averaged before being uniformly distributed to the downslope receiving subcatchment node, one must be very careful about the *a priori* assumptions of how each node is delineated and connected to subsequent nodes. The routing within SWMM is not based on hydraulics, but rather on a non-linear reservoir hydrologic method that has been shown to be less accurate, especially for predicting hydrographs for smaller storms where the event duration is less than the time of concentration (Xiong and Melching 2005). Although groundwater flow is included an option within SWMM, it analyzes groundwater flow for each defined subcatchment independently (Rossman 2015). This means that interactions between two infiltration areas can only occur if the water table has risen to the surface in the upslope area and runoff is produced by saturation excess.



Allowed Interaction between Infiltration Areas	Overland Flow Routing	Groundwater Model Specification	Example Testable Hypothesis
• If upslope infiltration rate or storage is exceeded, saturation overflow to downslope GI facility	• Lumped within sub-catchment • Hydrological routing : non-linear reservoir method • Less accurate, especially for time< time of concentration	• Moisture in unsaturated zone is averaged, there no shape (lens) • No lateral groundwater flow	• Does implementation of run-on infiltration decrease runoff volumes from impervious areas?
• In addition to above, interactions through shared groundwater table (results in Variable Source Area)	• Distributed within sub-catchment • Hydrological routing: assumes hydraulic gradients follow topography (no hydrographs produced)	• Simple, linear reservoir groundwater model	• How does the position of GI within the watershed (upslope or downslope) affect catchment scale effectiveness?
• In addition to above, lateral groundwater interactions between infiltration areas (mounding)	• Distributed within sub-catchment • Hydraulic routing: kinematic wave (dynamic wave also available) • Most accurate, most computationally intense	• 3-D variably saturated groundwater flow	• How does spatial clustering of multiple run-on infiltration facilities affect catchment scale effectiveness?

Figure 4.2 Conceptualization of various hydrological models' treatment of overland flow routing and groundwater and example testable hypotheses.

The Regional Hydro-Ecological Simulation System (RHESSys) model, which was originally developed for forested catchment areas, is spatially distributed and includes energy-water fluxes both between the surface and subsurface and the surface, plants and air. Although this model has been adapted for use in low and medium density developed catchments (B. C. Miles 2014), it is not suited for modeling higher density development because it lacks a solution to hydraulic flow routing (kinematic, diffusive, or dynamic wave), therefore it does not predict hydrographs. The groundwater model in RHESSys is a simple linear reservoir. In addition to the effect of saturation overflow from an upstream area, RHESSys therefore also allows for consideration of return flow and subsurface storm flow contributions to the measured response. With respect to GI implementation, this would allow for testing of upslope versus downslope positions of GI within the catchment (Tague and Pohl-Costello 2008; Mittman 2009; B. C. Miles 2014). In **Figure 4.2**, the diagram for RHESSys shows that the common subsurface reservoir has already affected the infiltration capacity of the downslope GI facility, despite the fact that the upslope facility has not yet “overflowed.”

ParFlow is a three-dimensional, variably saturated groundwater flow code, has been integrated with a two-dimensional overland flow simulator (Kollet and Maxwell 2006). The structure of this model is such that it does not necessitate the often awkward parameterization of a gradient across the surface-subsurface interface and the proportionality constant that has been typical of coupled surface-subsurface systems. Instead, it links the system of equations through the boundary condition at the ground surface, such the overland flow equations are implemented into the Richards equation at the top boundary cell under saturated conditions (Kollet and Maxwell 2006). This generalization of the surface-subsurface interaction results in both greater numerical stability and a continuous solution for pressure head. Since ParFlow is spatially distributed, integrates 3D subsurface- 2D surface interactions, and includes the solution for the kinematic wave approximation for shallow overland flow, this makes it an ideal candidate for testing under what conditions the position and configuration of GI within the subcatchment may be less efficient than the sum of the expected performance of individual GI facilities.

The need to account for the ecohydrological dynamics of meteorological forcing, evapotranspiration and subsurface flow described above to better represent dynamics that might affect UVSA, motivates the use of a high-resolution coupled surface-groundwater flow ecohydrological model, ParFlow.CLM (Kollet and Maxwell, 2006). ParFlow.CLM is capable of modeling these processes at high resolution in three dimensions in the subsurface through a finite-difference solution of the Richards equation in a grid-based domain. In contrast to other urban hydrological models that do not represent the three dimensional subsurface, ParFlow's use of Richards equation represents the most rigorous approach to calculating three dimensional movement of water in soils. **Table 4.1** illustrates in more detail how ParFlow's treatment of infiltration compares to two other hydrological models in common use for urban areas, RHESSys and SWMM.

While ParFlow uses a nonlinear solver to find the finite-difference solution of the full Richards equation (with the option to use van Genuchten lookup table to relate hydraulic conductivity to both pressure head and soil moisture to speed up calculations), RHESSys uses a simplification of Richards equation that assumes that hydraulic conductivity is dependent on moisture content, but not on pressure head, called Phillips equation. SWMM includes two main options for representing infiltration. One is a further simplification of Richards equation that assumes that conductivity is not dependent on either pressure head or soil moisture content, called Horton's equation. The other option for representation of nonlinear infiltration capacity in SWMM is based in an approximate theory which assumes a sharp, discontinuous wetting front as infiltration progresses (Green-Ampt method). In the Green-Ampt method, infiltration rate is expressed as an implicit function of cumulative infiltration.

Table 4.1. Comparison of governing equations and subsurface process representation in three hydrological models

Model	**ParFlow**	**RHESSys**	**SWMM**
Conservation of mass and momentum	Richards Equation	Phillips Equation	Horton's Equation or Green-Ampt Equation
Assumptions	Hydraulic conductivity and diffusivity are functions of soil moisture and pressure. Richards equation is solved for all grid cells throughout the entire domain.	Hydraulic conductivity and diffusivity are functions of soil moisture content, but not pressure head.	Horton: Hydraulic conductivity and diffusivity are constants, not dependent on soil moisture content or pressure head Green-Ampt: Implicit solution to infiltration (based on cumulative infiltration) that assumes sharp discontinuity at wetting front
Representative Equation	**Richards**: $\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x}\left(K(h)\frac{\partial \theta}{\partial x}\right) + \frac{\partial}{\partial y}\left(K(h)\frac{\partial \theta}{\partial y}\right) + \frac{\partial}{\partial z}\left(K(h)\frac{\partial \theta}{\partial z}\right)$ $K(h) = K_s S_e^l \left[1 - \left(1 - S_c^{\frac{1}{m}}\right)^m\right]^2$ $S_c = \frac{\theta(h) - \theta_r}{\theta_s - \theta_r}$ θ_r is residual water content θ_s is saturated water content S_e^l is the effective saturation *K* is hydraulic conductivity, a function of pressure head (*h*) *t* is time *z* is elevation head *h* is pressure head	**Modified Phillips**: $f(t) = \frac{1}{2} S t^{\frac{-1}{2}} + K$ $F(t) = S t^{\frac{1}{2}} + Kt$ *f* is infiltration rate *F* is cumulative infiltration *S* is sorptivity, a function of soil suction	**Horton:** $f(t) = f_c + (f_0 - f_c)e^{-kt}$ f_c is a constant infiltration rate f_0 is the initial infiltration rate *k* is a decay constant

Domain discretization	Three dimensional grid	Model has three vertical layers: surface detention, unsaturated zone and saturated zone. K_{sat} at the wetting front is used that is based on an exponential profile (K_{sat} decreases exponentially as depth increases). For vertical unsaturated zone drainage into saturated zone, K_{unsat} can be determined by the vanGenuchten method	Two-zone groundwater model with saturated and unsaturated zones.
Antecedent Moisture	Gridded continuous	Lumped – uniformly distributed in unsaturated zone	Lumped – uniformly distributed
Hydraulic Conductivity Profile	vanGenuchten look up table for full solution to Richards equation	Exponential profile	NA
Dimensions	Three	One	One
Lateral Subsurface Redistribution	Gridded Cell – Fully Distributed	TOPMODEL or DHSVM – quasi distributed at hillslope or basin scale, respectively	NA

ParFlow simulates coupled subsurface-surface flow through an overland flow boundary condition represented through a version of the kinematic wave equation when pressure head at the top layer of the domain is greater than zero. The CLM (Community Land Model) portion of the model represents surface-atmosphere dynamics including soil moisture and temperature, plant evapotranspiration and sensible heat flux (Ashby and Falgout, 1996; Oleson, 2010; Condon and Maxwell, 2014). ParFlow.CLM is efficiently optimized to perform on parallel resources, but has not been applied extensively to small urbanized sewersheds to “untangle” various ecohydrological processes (Bhaskar *et al.*, 2015).

APPLICATION OF PARFLOW.CLM TO A MEDIUM—DENSITY URBAN SEWERSHED

Site Context

In this chapter of the dissertation, I apply a ParFlow.CLM, a model that explicitly accounts for these dynamics to an urbanized, instrumented sewershed located in Washington DC’s Lafayette neighborhood. A sewershed refers to the area draining to a point within a storm drain or sewer collection system, similar to the idea of a 'watershed' but accounting for changes in contributing area due to built infrastructure systems. The purpose of the application of this model is to test the extent to which the spatial configuration of imperviousness and green infrastructure retrofits, in addition to the magnitude of retrofits, in existing urban environments affects the hydrological response from the area.

Since the EPA's acceptance of GI and source control technologies for reducing combined sewer overflow events, many cities with aging drainage infrastructure are seeking to incorporate GI planning into their CSO Long Term Control Plans (LTCP) as a cost effective way of complying with the CWA while also enhancing the livability of the urban environment. In 2015, DC Water, the Water and Sewer Authority and permit holder for the CSS outfalls in Washington DC was successful in amending its original LTCP to incorporate significant amounts of GI retrofits in selected sewersheds. In some sewersheds, runoff from up to 30% of impervious area will be treated through source control measures such as rain gardens, permeable pavement and bioswales. Implementation of this plan allowed for the downsizing of two previously proposed large, underground storage pipes, saving the District sewer and water ratepayers an estimated $475 per year through 2032 (DC Water, 2015). In Philadelphia, the EPA approved the most aggressive GI-based CSO LTCP in the US. Philadelphia's CSO LTCP, called "Green City, Clean Waters" (GCCW) calls for the city to construct 10,000 "Greened Acres" by 2030, where a "greened acre" is defined as the management of 1" of runoff from 1 acre of directly connected impervious surface (Philadelphia Water Department, 2009). 10,000 acres of imperviousness is nearly one third of the total area of the portion of the city served by the CSS. Unlike DC's LTCP, which identifies target percentage retrofits for specific sewersheds in the city, Philadelphia's GCCW was permitted solely in terms of aggregate area treated and does not address differences in capacity of the existing infrastructure.

The aggregate magnitude-based targets in Philadelphia and DC both do not consider the possibility that as an aggregate network, infiltration-based GI could potentially function differently than the sum of individual site-scale BMPs, or that the spatial configuration of this network might affect how it alters the urban hydrological cycle.

RiverSmart Washington monitoring program description

In this research I partnered with Washington DC's Department of Energy and the Environment (DOEE) on a project called the RiverSmart Washington project that evaluates a monitored urban sewershed before and after GI installation. DC's RiverSmart programs were established to help reduce stormwater runoff from entering the District's waterways and the Chesapeake Bay and to restore ecological function to the landscape. In 2015, Washington DC's water and wastewater utility provider, DC Water, revised its Combined Sewer Overflow (CSO) Long Term Control Plan (LTCP) to include GI components that allowed it to dramatically downsize two previously planned underground tunnels. This increased regulatory and institutional support to better understand the physical function of GI configurations and the effects of alternative site development morphologies at the sewershed scale (DC Water, 2015). In particular, city-wide initiatives to promote voluntary residential adoption of subsidized rain gardens and permeable pavement installations motivated a need to better understand how resulting spatial configurations may perform compared to facilities in the right-of-way (ROW), which may be more costly to the city.

Made possible through $4M in joint funding from the U.S. Fish and Wildlife Service, DOEE, and DC Water, DOEE began the RiverSmart Washington monitoring program in 2009. The project first monitored in-pipe flows for the base case, pre-GI condition for six months (from July 2010 to December 2010) as well as local precipitation monitoring. This initial monitoring period was followed by extensive construction of GI within several sewersheds in DC. At the Lafayette demonstration site (0.05 km2, and originally 34% impervious, with 15% building footprint and 19% pavement), the District Department of Transportation (DDOT) oversaw installation of bioretention bump-outs and permeable pavements designed to treat nearly all of the public ROW. **Table 4.2** below shows an inventory of the public right of way retrofits total surface areas and contributing areas. Measurements were calculated from the construction documents provided to me by DOEE and dimensions of the constructed facilities were verified in the field. Since construction documents did not include explicit delineation of contribution areas I mapped contributing areas in the field on November 28, 2015 based on visual flow paths during a rain event and site topography **Figure 4.3** shows site photographs of BMPs constructed in the public ROW during a rain event.

Table 4.2 Inventory of public right-of-way BMPs implemented on the site

Description	W (m)	L (m)	BMP footprint (m2)	BMP Contributing Area (m2)
Permeable Pavement - ROW Gutter	1.8	76.2	139.4	195.1
Permeable Pavement - ROW Gutter	1.8	70.4	128.8	149.4
Pemeable Pavelemt - Full width of alley	4.3	48.5	207.1	0.0
Bioswale - curb inlet extends off ROW	2.7	12.8	33.9	105.8
Permeable Pavement - ROW Gutter	1.8	48.2	88.1	112.1
Permeable Pavement - ROW Gutter	1.8	87.6	160.1	227.1
Bioswale in existing ROW	1.4	29.6	41.5	168.1
Permeable Rubber Sidewalk	1.5	58.8	89.7	0.0
Bioswale all outside ROW	1.6	16.5	27.2	312.5
Permeable Pavement - ROW Gutter	1.8	74.2	135.7	152.0
Permeable Pavement - ROW Gutter	1.8	54.6	99.8	143.2
Bioswale – curb inlet extends off ROW	2.9	12.9	37.6	112.7
Permeable Pavement - ROW Gutter	1.8	28.7	52.5	73.2
Permeable Pavement - Center of alley	1.2	56.2	68.5	102.7
Permeable Pavement - Center of alley	1.2	70.1	85.5	128.2
Permeable Pavement - ROW Gutter	1.8	111.6	204.0	254.3
Permeable Pavement - ROW Gutter	1.8	111.6	204.0	292.1
Permeable Pavement - Center of alley	1.2	104.6	127.6	350.8
Permeable Pavement - Full width ROW	9.3	41.9	389.9	0.0
Bioswale all outside ROW	1.4	13.7	19.5	66.1
Total			**2340.2**	**2945.5**

Figure 4.3 Site photographs of BMPs treating the sewershed's public ROWs. Top left: Permeable asphalt: surface runoff is visible, indicating lower than expected infiltration performance. Top middle: a bioswale with a flush curb cut extending beyond the ROW into adjacent grass strip. Top right left: permeable concrete installed in the center of a reverse crowned alley. Lower left: permeable concrete spanning the full width of the ROW. Lower right: foreground shows permeable rubber sidewalk adjacent to bioswale. Permeable pavers in parking lane are visible in the background.

GI retrofits were also constructed on private properties of willing residents. Of the 74 households within the sewershed, 25 agreed to install subsidized GI on their properties, resulting in the disconnection of over 1,400 m^2 of residential rooftop and over 550 m^2 of private paths and driveways. On my November 28, 2015 site visit, I mapped private pavement and roof areas that were re-routed to installed rain gardens or permeable pavement adopted by residents. Before 2010, residential downspouts were all physically connected to the storm drain system by a buried PVC pipe that drained either directly into the street or the adjacent sidewalk (see **Figure 4.4**).

Figure 4.4. Image of how roofs are directly hydraulically connected to the stormdrain via downspout, buried PVC pipe that drains to a sidewalk, which drains onto the street. Water is eventually flows into a curbside catch basin, which leads into the stormdrain.

Residents choosing to participate in the RiverSmart Washington retrofit program were offered a selection of potential BMPs that included: permeable pavers, rain gardens, bayscaping (native landscaping), and rain barrels. In order to increase participation rates in this neighborhood, DOEE offered residents subsidies for these retrofits above those offered to residential participants in the city-wide residential RiverSmart Homes retrofit program (described in more detail in Chapter 6). **Table 4.3** shows an inventory of residential retrofits and site summary statistics. Retrofits are grouped based on intended function: rain barrels serve the function of disconnecting roofs from the storm drain; bayscaping and rain gardens increase the permeability and porosity of native soils through amending soils; permeable pavements increase permeability of impervious surfaces.

Table 4.3. Inventory of private GI retrofits

Sewershed Total Area	52,000 m^2
2010 Total Impervious Area	22,000 m^2 (42%)
Total Private Property Area	37,000 m^2 (71%)
Number of Parcels	74
Lot size Min Max Median Mean	 5 m^2 1,490 m^2 528 m^2 499 m^2
Disconnected Roofs (draining to rain barrels, rain gardens, permeable pavement, or lawn)	1,423 m^2
Treated Pavement (permeable pavement)	552 m^2
Amended Lawns (rain gardens and bayscaping)	195 m^2
Lawns to impervious (residential renovations)	205 m^2

Construction of all the retrofits was followed by ten months of post-GI installation flow monitoring. This before and after monitoring dataset at the sewershed scale is unique and can be used to evaluate the retrofits' impact on physical ecohydrological processes within the sewershed. **Figure 4.5** depicts the boundary of the sewershed with locations of public and private GI installations and the monitoring location.

Figure 4.5. Domain of the study sewershed with public and private installations of GI and monitoring locations. Building footprints and sidewalks are in brown; streets are in gray; pervious areas are indicated by pale green; dark blue indicates public GI projects; dark green indicates private GI projects; the red arrow points to the monitoring location.

The before and after flow monitoring was carried out using ADS Flowshark installed directly in the storm drain pipe, located underneath 34th street (red arrow shown in **Figure 4.4**). The flow meters employed four ultrasonic level sensors to record stage (water level height) data in the pipe, a digital Doppler velocity meter, and a pressure sensor to measure surcharging conditions and provide additional stage data. Data from the meters were transmitted wirelessly via cellular communications. Local rain data were also collected via a tipping bucket rain gauge installation located at MacFarland elementary school. The collected raw stage flow data were cleaned and used to calculate 5 minute increment instantaneous flow and paired with the rain gauge data. Data for the before and after monitoring activities were compiled by ADS and provided to the RiverSmart Washington subconsultant, Limnotech.

LOCAL AND REGIONAL METEOROLOGICAL AND GEOPHYSICAL DATA SOURCES

ParFlow allows the user to specify the number of desired subsurface layers in the model, with a minimum of 10 layers for coupling with the evapotranspiration and land surface-atmospheric model CLM (Community Land Model) (Oleson, 2010). There are multiple ways the subsurface can be specified in ParFlow: through the creation of a “solidfile” with constant dz discretization, or a terrain following grid (TFG), which can be paired with variable dz discretization. Although the variable dz discretization is more computationally intensive (and requires additional post-processing steps to correctly scale the model’s output results), the variable dz option allowed me to represent finer-scale dynamics in the near surface layers with a small dz, and deeper layers with larger dz thicknesses, decreasing the total number of layers in the model and considerably saving total computational resources (Maxwell, 2013).

Although I did not anticipate sewershed-scale GI retrofits to have an effect on regionally-determined groundwater levels, I chose to define my subsurface domain with 12 variable dz layers in a terrain following grid extending to a total depth of 50 m below the surface. Including this depth in the model increased the stability of the underlying water table and prevented positive pressure buildup in low-lying areas of the site, which were confirmed not to exhibit presence of groundwater within 2 m of the surface. This was because there is a 21-m elevation differential across the site and well data from the nearest wells indicate water table depths that have varied between 5.2 m (17.6’) and 6.4 m (21.0’) below the land surface for the past 15 years (**Figure 4.6**). In order for the lowest point of the site to maintain at least 5 m depth to groundwater, at least 26 m depth on the side of the domain with higher elevations had to be provided so that the water table was ensured to always be within the domain. This point is further explained below in the Regional Geologic Properties and Model Spinup sections. After the total model domain depth of 50m was established, the domain was divided into 12 layers (using the TFG specification of ParFlow), with layer thicknesses based on a combination of desired resolution based on expected dynamics of subsurface flow and empirical layer depths. The final thicknesses for the twelve layers were, from topsoil/pavement to bedrock: 0.05m, 0.05m, 0.05m, 0.5m, 0.5m, 0.5m, 0.75m, 2.5m, 5m, 5m, 10m and 25.1m.

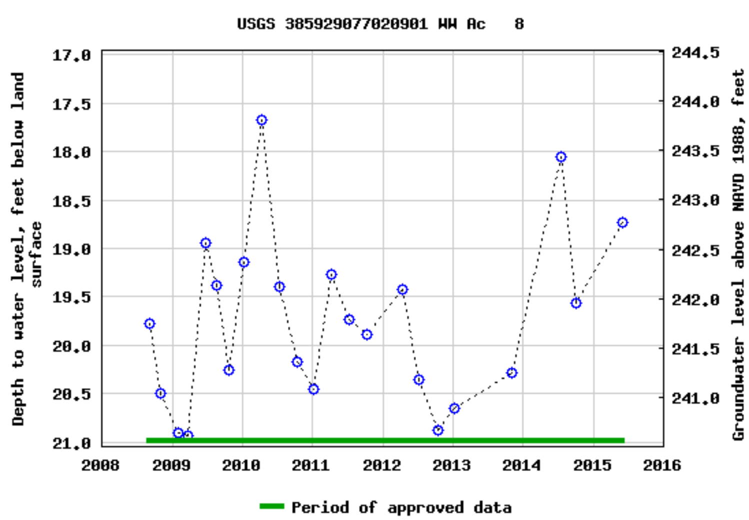


Figure 4.6. Temporal variation of water table depths from a nearby well, also located in the Piedmont Physiographic Region to the north of the site.

A summary of geophysical parameters of the site and their sources are summarized in **Table 4.4.** The following sections provide additional detail on these data.

Local Geotechnical Reports

As part of the extensive DDOT GI construction, geotechnical analyses of 32 boring locations distributed throughout the site were carried out and provide much detail on the hydraulic conductivity conditions of the site to 2-m depth (HSA, Inc, 2012). Geotechnical reports included sieve analyses from 2 depths for each boring: between 1.2m – 1.8m (4' – 6'), and between 1.8m – 2.4m (6' – 8'). From the sieve analyses' particle distributions, I calculated the mean tenth percentile passing (d_{10}) across the 32 borings at each of the two sample depths. The geotechnical reports include depths of defined strata (topsoil, asphalt, concrete, estimated fill, and native soil) for each boring, soil descriptions (sand, silt, clay composition), and results for two sieve analyses for each boring location. Hydraulic conductivity for depths between native soils and backfill up to the depth of 2.44 m (8 ft) were calculated based on the results of the HSA sieve analysis, using the Hazen formula (Vienken and Dietrich, 2011):

$$K_s = C_H * d_{10}^2$$

Where the units of hydraulic conductivity (K_s) are cm/s, C_H is the Hazen coefficient (1), and d_{10} is in mm. This resulted in permeabilities (hydraulic conductivities) of 8.14 x 10^{-6} m/h for the top soil layer (soil 1), and 5.42 x 10^{-6} m/h for the lower soil layer (soil 2).

The thicknesses of the variable dz layers in the subsurface domain are constant across the horizontal domain. The geotechnical reports focus on conditions within the public ROW and in alleys, since this is where the design of public BMPs were located. However a few borings were located in the turf strip between the ROW and the sidewalk. These borings indicated that in pervious areas, the average topsoil thickness was 5 cm (2.0 in).

Paved ROWs and alleys either have asphalt or concrete surfaces. In asphalt covered ROWs/alleys, underlying 7.6 cm (3 in) of asphalt is approximately 23 cm (9 in) of aggregate base. Concrete used in alleys is 23 cm (9 in) thick. There is no aggregate fill underlying concrete-surfaced alleys. In some cases, there is some evidence of backfill underlying the ROWs and alleys and the geotechnical reports give estimates of these thicknesses. However, since the reports also state the fill is compositionally and visually very similar to the surrounding native soil, I assumed that the fill properties are similar to the shallower of the two soil analyses performed at each boring location. The first 0.15 m (6 in) of the subsurface domain in ROWs and alleys is therefore defined as pavement. The properties of underlying aggregate base layers are averaged with areas of thicker imperviousness and assigned the hydraulic properties of native soils as determined by the sieve analyses.

Topsoil was assigned a hydraulic conductivity $K_s = 3.75 \times 10^{-4}$cm/s and porosity 0.4, based on the mean of field-measured values in an urban environment in nearby urban Virginia (Chen *et al.*, 2014). Impervious pavement (both asphalt and concrete) were assigned $K_s = 8.5 \times 10^{-7}$ cm/s and porosity of 0.1% based on values reported in the literature for measured hydraulic properties of asphalt (Kuang et al., 2011).

The soils underlying pervious areas are assumed to be native soils. According to the reports, even where fill has been placed, it apparently has been composed mostly of native soils, making it difficult to differentiate strata. Therefore, hydraulic properties for soils underlying the topsoil are assigned in the same manner as described above for the first sieve analysis layers. Underlying either topsoil or pavement layers therefore are either 2.35 m of soil 1 and soil 2 properties or 2.25 m of soil 1 and soil 2 properties, discretized into layers as shown in **Table 4.4**.

Regional Geologic Properties

Beyond the 2.35 meters of site-specific geotechnical reports defining the soils properties of the site, deeper soil hydraulic properties were defined from regional data. The Lafayette study site is located in Northwest, Washington DC. DC is bisected by the Fall Line, which delineates the Atlantic Coastal Plain (east) and Piedmont (west) physiographic provinces. The Lafayette site is located within the Piedmont physiographic region. This was confirmed both by Maryland State Geologic Survey and by the site engineer's geotechnical reports (HSA, Inc, 2012). The Piedmont physiographic province is defined by layers that include soil, saprolite, a transition zone of highly weathered bedrock, and fractured bedrock.

I defined layer thicknesses based on regional geological survey reports. The length of well casing is a commonly used method of approximating the depth of the soil, saprolite and transition zone layers, since well casings usually extend to within 0.6 m (two feet) of the bedrock layer. Maryland has several reports that use this method to determine the depth of the saprolite layers in the Piedmont physiographic region. Burgy and Duigon (2012) and Nutter and Otton (1969) report that in Maryland, well casing lengths range from 0 to 30.5 m (100 ft) in depth, with an mean thickness of 12.5 m (41 ft).

Underlying the saprolite layer is a transition zone of weathered bedrock that is characterized by high hydraulic conductivity. In the North Carolina Piedmont physiographic region, which is of the same geologic composition as the Piedmont underlying Washington DC, the transition zone has been estimated to be 4.6 m thick (15 feet) (Harned and Daniel, 1992). Because in reports for well casing depths in Maryland, the transition zone is not specifically delineated from the saprolitic layer, it was assumed to make up a 5 m thick (16.4 ft) layer, the top third of which is within the 12.5 m (41 ft) of the surface. The remainder of the 12.5 m mean well casing depth (7.5m) was assigned to saprolite. The transition zone is underlain with bedrock layers to a total subsurface depth of 50 m (164 feet).

There were several sources of hydraulic properties for the saprolitic layers. Nutter and Otton report transmissivity values for pumped and observation wells in the Maryland Piedmont for saprolite ranging in thickness from 18.3 m – 25.3 (60 ft – 83 ft). Transmissivity coefficients were converted to estimates of hydraulic conductivity by dividing by the thickness of the saprolite. The average of all the calculated hydraulic conductivity values (1.43 E -03 cm/s) was assigned to the upper saprolite layer in the model. Nutter and Otton also report hydraulic conductivity values for saprolitic layers specifically for the Wissahickon Formation (of the Lower Peletic Schist geologic formation) for saprolite ranging in depth from 1.3m to 5.0m (4.5 ft – 16.5 ft). These values ranged from 5.70 E-04 to 1.14 E-03 cm/s (1969). Green *et al.* (2004) reported a hydraulic conductivity value for saprolite of 3.53 E-04 cm/s, and the average of the Nutter and Otton reported values and the Green value was applied to the lower saprolitic layer in the model (1.78 E-03 cm/s).

Layers below 10 m (33 ft) are defined as the transition zone and fractured bedrock layers (Cunningham and Daniel, 2001). Hydraulic conductivity values for the high-fracture/hydraulic conductivity transition zone layers were calculated based on specific capacities reported in the Maryland Piedmont by Nutter and Otton (1969) and an empirical formula relating specific capacity to transmissivity reported by Mace (1997) and the dividing by the thickness of the overlying regolith.

$$T = 0.76S_c^{1.08}$$

where T is the transmissivity (L^2/t) and S_c is the measured specific capacity (L^2/t). Calculated hydraulic conductivities for depths up to 61 m (200 ft), were averaged to obtain the hydraulic conductivities to apply to the transition zone.

Hydraulic conductivity in the bedrock layers are dominated by flow through fractures, which decrease in density as bedrock depth increases. I assume that the exponential decrease in hydraulic conductivity as a function of depth in fractured bedrock is functionally similar to the exponential decrease in well yields with well depths (Paulachok, 1991), as has been done by others (Andino, 2015). The following empirical relationship has been established for the Wissahickon formation, to which the site belongs.

$$y = a * x^{-1.017}$$

where y is well yield (gallons per minute), x is depth in feet, and a is an empirically determined constant. I assume that hydraulic conductivity has a similar relationship to depth:

$$K_s = b * x^{-1.017}$$

where K_s is in m/hr and x is in meters. The K_s value 6.99×10^{-3} for the uppermost fractured bedrock layer was obtained from the median hydraulic conductivity of the Oligoclase-Mica Schist of the Wissahickon formation (although the sites are classified as “Lower Peletic Schist” within the Wissahickon formation, this classification was formerly mapped as oligoclase facies and are therefore assumed to have similar properties) (Low *et al.*, 2002). This K_{sat} value and a depth of 30 m was then applied to the above expression and solved for b ($b = 0.214h^{-1}$). Porosity values for the saprolite, transition zone and fractured bedrock layers were assigned using a porosity curve in the Piedmont region of North Carolina (Figure 4, p 9, (Cunningham and Daniel, 2001)), as summarized in **Table 4.4**.

Vegetative and Impervious Cover

A high resolution vegetative cover dataset was provided to me of the DC metro area by researchers at the University of Vermont (University of Vermont, 2011). This dataset had a 1 m resolution and included six land cover/vegetation classifications within the Washington DC area: base soil, buildings, roads/railways, other paved surfaces, tree canopy, and water. The CLM portion of the model, which controls meteorological forcing, energy fluxes, and evapotranspiration, requires all grid cells be assigned a vegetative cover classification (**Table 4.5)** (Maxwell *et al.*, 2016). In order to generate the vegetative cover input dataset to be used in the CLM portion of the model, the UVM land cover dataset was reclassified to three types of vegetative cover: tree canopy ("Deciduous Broadleaf Forest"), urban and built, and grassland. These land covers were mostly selected to represent the differences in tree canopy interception and fallthrough and evapotranspiration processes associated with different types of vegetation. Therefore, grid cells of both pervious and impervious surface types underlying tree canopy were assigned to the "Deciduous Broadleaf Forest" vegetative cover type. All other pervious surface was assigned to "Grassland" and impervious surfaces not underneath tree canopy was assigned to "Urban and Built." The tree canopy over the site is shown in **Figure 4.7**.

Table 4.5. Land cover classes used in CLM

1. Evergreen Needleleaf Forest
2. Evergreen Broadleaf Forest
3. Deciduous Needleleaf Forest
4. Deciduous Broadleaf Forest
5. Mixed Forests
6. Closed Shrublands
7. Open Shrublands
8. Woody Savannas
9. Savannas
10. Grasslands
11. Permanent Wetlands
12. Croplands

13. Urban and Built-Up

14. Cropland/Natural Vegetation Mosaic

15. Snow and Ice

16. Barren or Sparsely Vegetated

17. Water

18. Wooded Tundra

Figure 4.7. Land cover distribution on domain. Any areas underneath tree canopy were assigned "Deciduous Broadleaf Forest" for the CLM portion of the model. The figure above shows the areas under tree canopy in green. The boundary of the sewershed is shown in red.

The soil hydraulic properties shown in **Table 4.4** and Manning's n values, were based on a classification of land cover that included pervious areas, roofs/pavement, vegetation-based GI, and pavement-based GI. The impervious/pervious land cover classification used for both for defining the CLM vegetative cover and for the assigning hydraulic properties were rasterized from vector polygons of building footprints, and ROW boundaries from DC's Office of the Chief Technology Officer (OCTO). I delineated boundaries of private impervious areas (patios, paths, driveways) from aerial imagery from publically available ESRI basemaps. The basis of the final DEM used in the model was a 1m resolution base earth LIDAR digital elevation model also available from DC OCTO.

Meteorological Data

In addition to the site-specific rain depth data from Limnotech, I assembled meteorological data by combining site-specific precipitation monitoring from the RiverSmart Washington Program and National Land Data Assimilation Systems (NLDAS) meteorological forcing data (Mitchell, 2004), which additionally includes hourly records for air pressure, air temperature, wind speed, humidity and solar radiation retrieved for the site based on geographic coordinate-specified boundaries. The NLDAS data product used was "NLDAS Primary Forcing Data L4 Hourly 0.125 x 0.125 degree". The coordinate boundaries used to specific the spatial extent of the NLDAS data were: North: 38.968701; South: 38.950446 ; West: -77.077434 ; East: -77.053642. The two-dimensional data downloaded from NLDAS was further processed to a uniform one-dimensional hourly time step using code written in the ncl scripting language (https://www.ncl.ucar.edu/).

REPRESENTATION OF GREEN INFRASTRUCTURE BMPS IN DOMAIN

There were two major challenges of representing GI retrofits in ParFlow. The first challenge is the issue of surface flow routing. As mentioned above, interventions such as constructing a bioswale to intercept flows along the curb and gutter and disconnecting a roof downspout and directing the flows into a rain garden do not only change the fate of rain that falls directly on the retrofit; they also change the routing of rain that falls on areas contributing to the retrofit. **Figure 4.8** illustrates this for rooftops. In reality, the site has higher hydraulic connectivity than can be represented through a topography-based watershed model because of downspouts, buried gutters and the subgrade storm drain system. If building footprints are left were they appear in reality, water hitting the impervious roof would be intercepted by the lawn in the watershed model, when in fact, this area is directly connected to the storm drain. Thus, if no correction is made, “disconnection” by adding a bioswale in the model would have a muted effect compared to reality.

To correct for this problem, I made two major modifications to the original site data. First, to reflect the true routing of roofs to stormdrains, I physically moved the building footprints to be adjacent to the street. This better represents the base case scenario of rooftops immediately gaining hydraulic connectivity to the storm drain system without having to create subgrade flow paths in the subsurface to represent the buried PVC pipe. For roofs that are subsequently disconnected and routed to a rain garden (as shown in **Figure 4.8**), the portion of the roof that is disconnected is placed “upslope” of the installed BMP, while the portion of the roof that is still connected is left in the position adjacent to the ROW. Second, I apply a “burn” at the centerline of the ROW to represent the darinage pipe and to enforce drainage of the site towards the drainage infrastructure. “Burning in” the centerline of the street as a representation of the subgrade pipe is a technique that has been used for both small stream systems and for built infrastructure that has replaced first and second order streams in urban areas (Bhaskar *et al.*, 2015). The storm drain system on the site is separate from the site wastewater collection system. It is not pressurized and does not experience surcharging during rain events, therefore these simplifications treat the pipe as surface open channel flow.

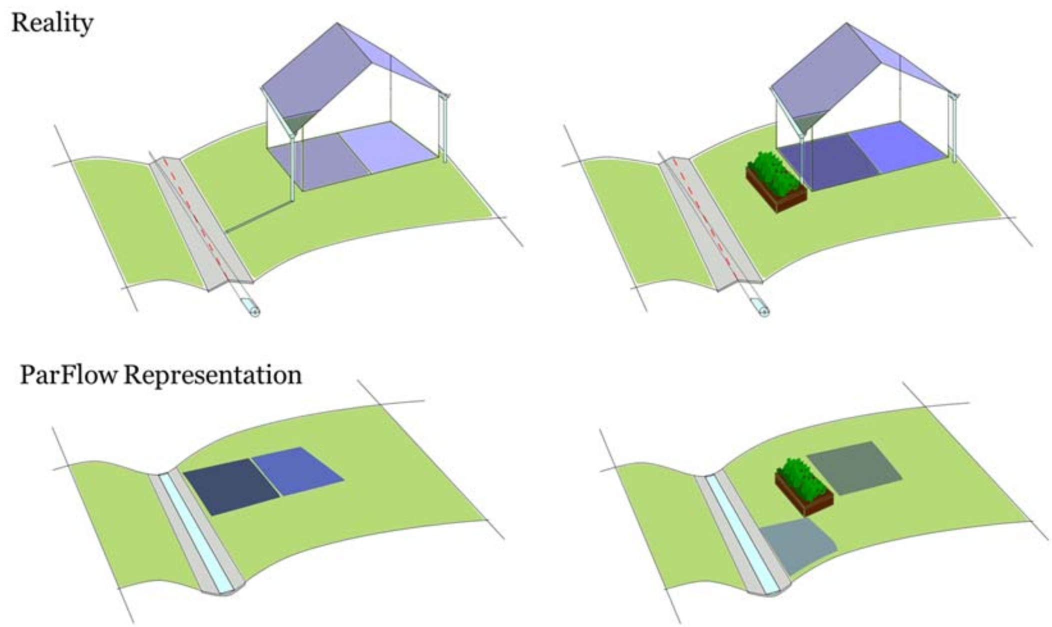


Figure 4.8. Conceptual illustration of representation of hydraulic connectivity of roofs with connected and disconnected downspouts, and "burned" in storm drain system.

The second challenge is representation of contributing area and GI footprint within the same grid cell. The horizontal resolution chosen for the domain is 5m x 5m. This means that for many of the GI retrofits both in the public ROW and on private property, one grid cell can exceed the actual area of the BMP's footprint (some of the smaller residential rain gardens have footprints close to 1 m^2). The solution to this problem is that a grid cell for GI retrofits actually represents the weighted average of hydraulic properties of both the BMP retrofit *and* its contributing area, according to the relative areas of each. For example, GI treating rooftops are sized to have 1/10 of the footprint of the contributing roof area, therefore, the hydraulic conductivity assigned to the treated area of the roof is (10*($K_{s\ roof}$)

+ $K_{sbiomedia}$)/11. The properties assigned for pavement-based GI and vegetated based GI are presented in **Table 4.4.** The hydraulic conductivities used for the weighted calculations were derived primarily from the District Department of Transportation construction specifications for backfill materials and the Hazen equation (from construction documents). Where specifications were not available, typical values from industry and academic literature were used.

Table 4.4 – Hydraulic Properties Assigned To Domain Subsurface Based on Land Cover Type

Land-Cover Specific Subsurface Layers

Layer	Thickness (m)	Depth to Bottom (m)	Description	Ksat (cm/s)	Porosity	Ksat Source/Method	Porosity Source/Method
Pervious							
1	0.05	0.05	Topsoil	3.75E-04	0.460	Chen *et al.* 2014 midpoint of reported range	
2	0.05	0.1	Soil 1	8.14E-06	0.400		Porosity curve from Cunningham and Daniel (2001)
3	0.05	0.15	Soil 1	8.14E-06	0.400	HSA Geotechnical Report; Hazen formula	
4	0.5	0.65	Soil 1	8.14E-06			
Impervious - ROW, Roofs							
1	0.05	0.05	Impervious	8.50E-07	0.001		
2	0.05	0.1	Impervious	8.50E-07	0.001	Kuang *et al.* 2011; lower end of reported range	Skelly and Loy, 2011; reported value
3	0.05	0.15	Impervious	8.50E-07	0.001		
4	0.5	0.65	Soil 1	8.14E-06	0.450		
						HSA Geotechnical Report; Hazen formula	Porosity curve from Cunningham and Daniel (2001)
GI - vegetated							
1	0.05	0.05	Bioinfiltration Media	3.25E-03	0.043		
2	0.05	0.1	Bioinfiltration Media	3.25E-03	0.043		
3	0.05	0.15	Storage	2.04E+00	0.068	Construction document specifications; Hazen formula	DDOT specification, AASHTO standard
4	0.5	0.65	Storage	2.04E+00	0.068		
GI - pavement							
1	0.05	0.05	Permeable Pavement	3.30E-05	0.010	Construction document specifications; Hazen formula	DDOT specification, AASHTO standard
2	0.05	0.1	Permeable Pavement	3.30E-05	0.010		

3	0.05	0.15	Storage	2.04E+00	0.068		
4	0.5	0.65	Storage	2.04E+00	0.068		

Common Subsurface Layers

5	0.5	1.15	Soil 1	8.14E-06	0.450	HSA Geotechnical Report; Hazen formula	
6	0.5	1.65	Soil 2	5.42E-06	0.470		
7	0.75	2.4	Soil 2	5.42E-06	0.470		
8	2.5	4.9	Saprolite	1.43E-03	0.470	Nutter and Otton, 1969; mean of reported	
9	5	9.9	Saprolite	1.78E-03	0.470	Nutter and Otton, 1969; Green *et al.* 2004; mean of reported	Porosity curve from Cunningham and Daniel (2001)
10	5	14.9	Transition Zone	3.58E-03	0.470	Nutter and Otton, 1969; Mace 1997; mean of reported transmissibility, divided by depth of regolith	
11	10	24.9	Bedrock	1.26E-04	0.050	Paulachok 1991, Low *et al.,* 2004; Andino (2015) well yields method	
12	25.1	50	Bedrock	8.25E-05	0.020		

BOUNDARY CONDITIONS AND MODEL SPINUP (INITIALIZATION)

“Model spinup” refers to the initialization period where the model reaches dynamic equilibrium, given the boundary conditions and meteorological forcing applied to the site. The TFG setup for ParFlow can be thought of as a box, with boundary conditions that are set for each of the six faces. Because of the topographic relief of the site and the fact that nowhere on the site does the groundwater table intersect the surface topography, constant pressure head boundary conditions were set on the eastern face (higher elevation) and the western face of the domain to allow water to drain from the subsurface directly (**Figure 4.9** shows the elevation range across the site). A 20 m different in pressure head between the eastern and western faces was set to represent the approximately constant empirical depth to groundwater in the Piedmont areas of the District. Zero flux boundary conditions were set on the northern, southern, and bottom faces of the box. An overland flow boundary condition and meteorological forcing conditions (precipitation, evapotranspiration) coupled through the CLM portion of the model were used for the top of the domain.

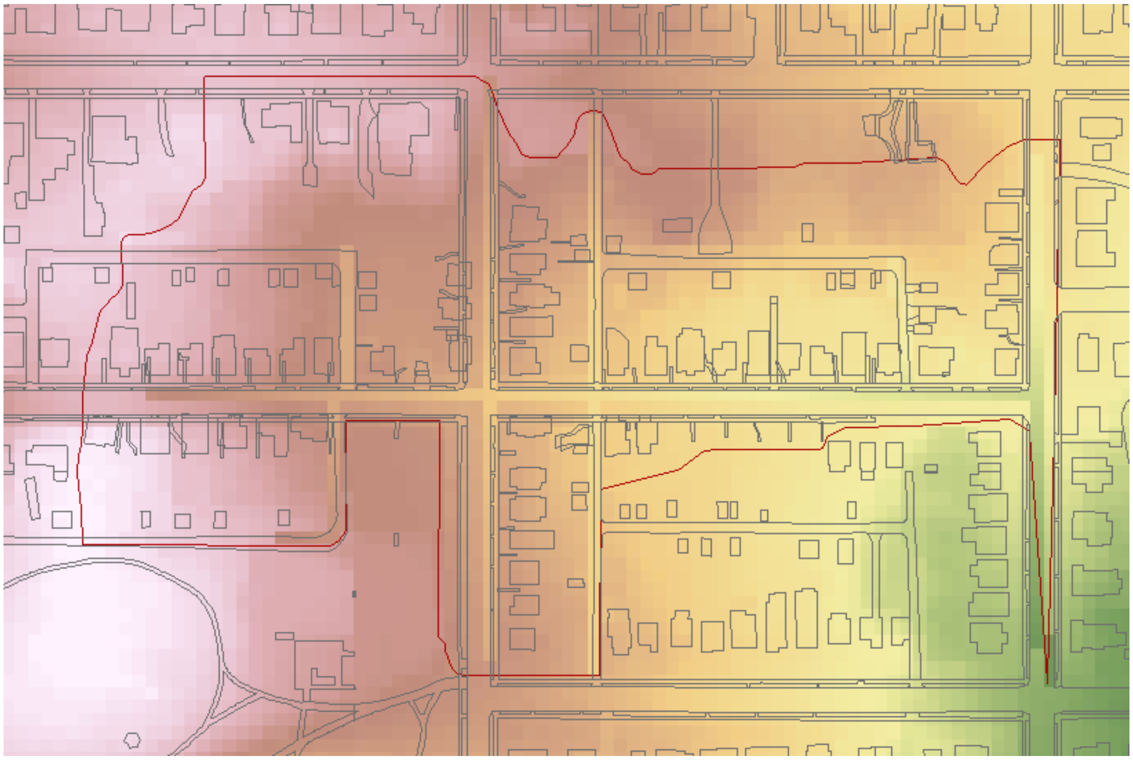


Figure 4.9. Site elevation, showing modified DEM with burned in street centerline. White= upper range of elevations, max = 118.1 m. Green = lower land of elevations, min = 93.2 m. Original positions of building footprints, private paths and driveways and ROW outlines are shown overlaid on the modified DEM.

Spinup was carried out in two stages. Through a process of trial and error, both these stages was found to be necessary in order for the KINSOL nonlinear solver to reach convergence for each time step of the simulation. In the first stage of spinup, the domain is set with an initial pressure of -15 m (from the surface) across the entire domain and the above described meteorological conditions. In addition, the first stage of spinup was done with homogeneous permeability three orders of magnitude higher than the permeability of the native soils. Permeability was increased throughout to get the water table to reach equilibrium throughout the domain faster. ParFlow r 743 includes spinup keys that remove positive pressure from the top layer, preventing the formation of any overland flow. This lowers the computational requirements of solving both overland flow and subsurface flow, which often occur at vastly different orders of magnitude, and sometimes result in convergence issues. This part of spinup was run for 365 model days, at 1 hour timesteps, and required a wallclock time of less than half an hour using 256 processors on the Texas Advanced Computing Center's supercomputer "Stampede." Specific aspects of the parallelization of the runs are discussed in the next section.

For the second stage of spinup, heterogeneous permeability was introduced into the domain, along with the CLM meteorological forcing and land-atmosphere model using hourly NLDAS data from 2009. The overland flow keys were again applied to suppress overland flow. The 2009 NLDAS data was run repeatedly for a total of eight years, until the year or year change in subsurface storage fell below 0.03%. **Table 4.6** shows the year on year percentage change in subsurface storage, and **Figure 4.9** shows the subsurface storage reaching a dynamic equilibrium by year nine of the stage 2 spinup. This stage of spinup took 20 hours using 256 processors on Stampede.

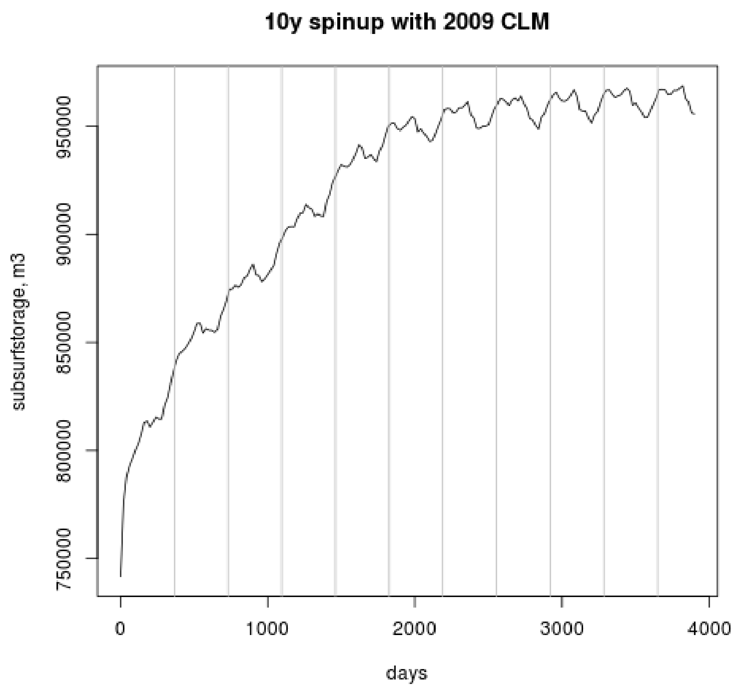


Figure 4.10 Dynamic equilibrium being reached after 8 years of spinup

Table 4.6 Percent change in volume of water in subsurface storage for first 8 years of spinup

Year	1	2	3	4	5	6		7	8
Percent Change in Subsurface Volume	4%	3.3%	2.5%	1.8%	1.1%	0.127%		0.0433%	0.026%

PARFLOW WORKFLOW

Running ParFlow and Run Efficiency Code Modifications

My application of the ParFlow.CLM model utilized the 743 release (https://github.com/parflow). ParFlow.CLM is optimized to make use of high-performance computing resources to simulate surface and subsurface flow, therefore the domain was split to make use of parallel compute cluster topology. All simulations in this study (including spinup and scenarios described in the following chapter) were run on 256 processors (16 nodes) on the “Stampede” computing cluster at the Texas Advanced Computing Center, accessed through the NSF Extreme Science and Engineering Discovery Environment (XSEDE) platform. The study area domain, which had a total of 69,120 cells, were distributed with 16 process splits in the x direction, 16 process splits in the y direction, and 1 process split in the z direction.

Modifications to the original ParFlow code were made to optimize run time on the compute cluster. During ParFlow simulations, if the nonlinear solver (used to solve finite difference differential equations of three-dimensional Richards equation) for any particular time step does not converge within a pre-specified number of maximum solver iterations, the original ParFlow software “cuts” the time step in an attempt to simplify the problem. The default cut factor in ParFlow is 0.5. If the cut time step is solved, ParFlow returns to the original nonconverged timestep to attempt another solution. In the case where several failed timesteps occur in a row (as was the case for when overland flow begins to form on the modeled land surface), this can result in forward and backward jumping between smaller and smaller increments and the failed time step, causing much inefficiency. I modified the original ParFlow timing code such that if one timestep did not converge, the time step was cut to a constant dt of 0.001, and increments proceeded forwards the original non converged time step was reached. This resulted in much higher stability and no instances of multiple time step cuts for any of the scenarios.

Model Calibration and Comparisons with Monitored Flows

The RiverSmart Washington Program collected in-pipe flow data before and after the construction of GI, which started in 2011. Because of the computational expense of running full simulation runs of ParFlow, several characteristic rain events from the before period were selected to calibrate the overland flow Manning's roughness coefficient (n). Manning's n was the only parameter selected for calibration to avoid issues of equifinality. The procedure for calibration followed was similar to that used in Bhaskar *et al.* (2015), where a runtime Mannings n was used for simulation, and several manning's n values were used to calculate overland flow in a post-processing script. The Manning's n values in the post-processing calculations that yielded the closest shape (rising limb and recession limb timing) and magnitude of peak flow to the observed hydrographs were selected for the subsequent calibration simulation. After several iterations, I determined that differentiating Manning's n between the impervious areas of the site and the pervious areas of the site was necessary to best capture the relatively immediate response to rainfall recorded at the in-pipe storm drain monitoring location, and the correct order of magnitude flow peak. **Figure 4.11** shows a comparison of simulated versus observed flows at the pour point (monitoring location) for several rain events that occurred in August 2010.

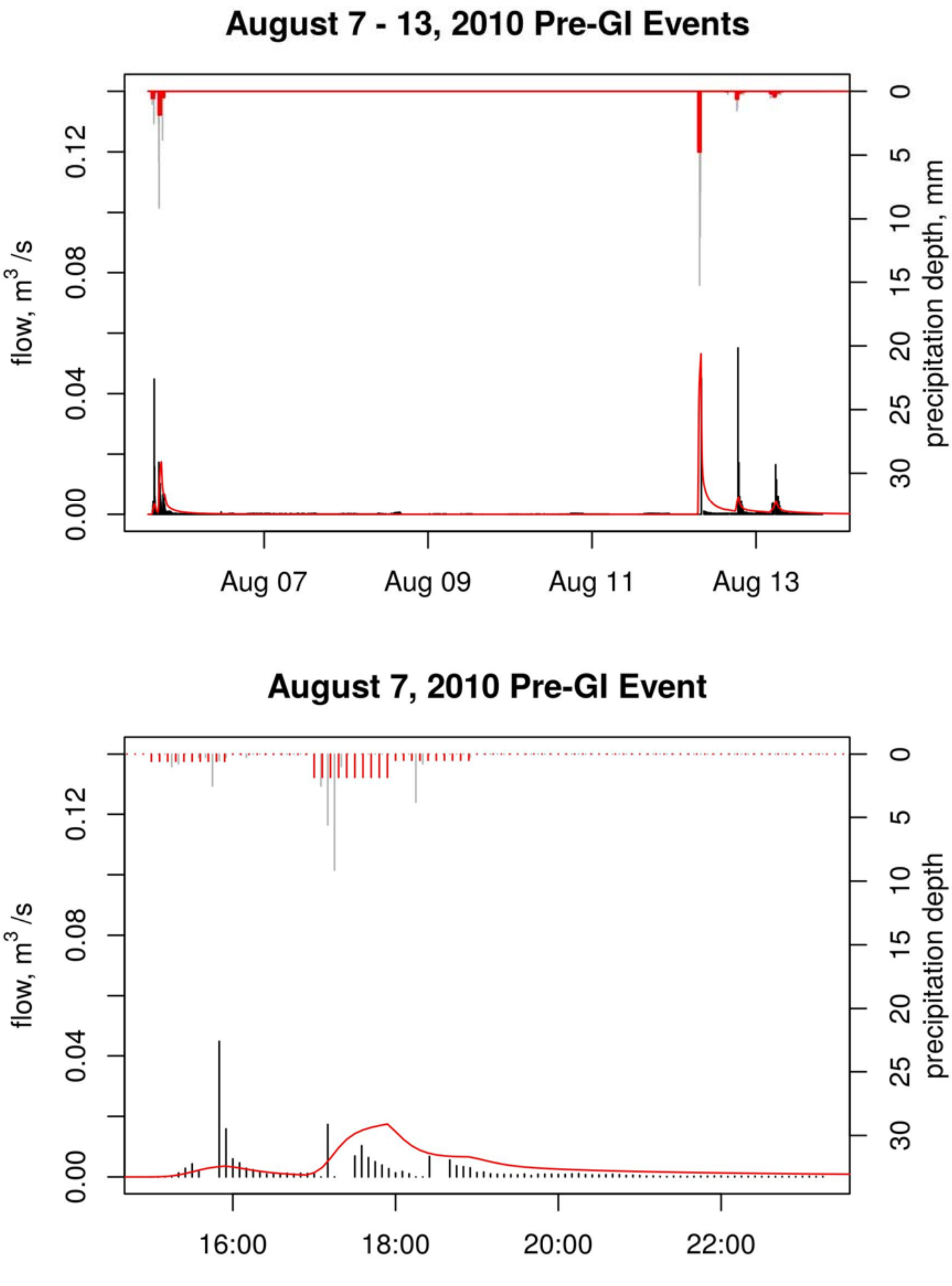


Figure 4.11. Final calibrated model output for overland flow at the monitoring location.

Several points became evident in the process of calibrating Manning's n. First, compared to the methodology used in Bhaskar *et al.* (2015), calibration had to be done more qualitatively in this study, and visual inspection of the calculated overland flow hydrographs' shapes and peaks became the main means of evaluation of the model's performance for each iteration of Manning's n. Factors of consideration included order-of-magnitude peak flows, immediate response in the rising limb (within the same 0.1 h time interval as the beginning of precipitation), and timing of the recession limb to return to near-zero "baseflow." As expected, higher values of Manning's n resulted in lower flow peaks and elongated recession limbs. Second, inconsistencies in the monitored data also became evident. An example of this issue can be seen in the top panel of **Figure 4.11** for the August 7 – 13, 2010 rain events. The simulated overland flow very closely matched the observed overland flow for the first pulse of 47 mm total rain depth (observed peak flow = 0.055 m^3/s; simulated peak flow = 0.050 m^3/s). However, for the two subsequent pulses of rain (depths = 7.35 mm and 6.1 mm , respectively), the second observed peak of the same order of magnitude as that for the first pulse (0.0164 m^3/s), and the third observed peak is also higher than expected (0.0403 m^3/s). The simulated flows, by comparison more closely reflect the relative orders of magnitudes in flows that we would expect to see from the relative volumes of rainfall observed (second pulse flow = 0.0058 m^3/s, third pulse flow = 0.0043 m^3/s)

A third issue that became evident was the effect of the use of hourly meteorological forcing data compared to 5 min timestep data. As was explained in a previous section, the inputs to the CLM portion of the model need to be provided at an hourly timestep (dt = 1h). When the model is run on a shorter timestep, as is the case for my application of ParFlow, where dt = 0.1 h, the rainfall rate (LT^{-1}), is divided into 10 even increments over 1 h. This means that if the majority of a rain event occurred within one 5 min interval in reality, this rainfall depth would be spread evenly across 10 0.1-h dt timesteps, resulting in lower intensities, but preserving the total volume of rainfall on the site for the event. Some of this effect can be observed from a comparison of the observed and simulated rainfall depths in the bottom panel of **Figure 4.11**. In the second pulse of rain, the observed rainfall (recorded at 5 min intervals) occurs within three 5-min intervals, but this total volume is spread over 10 6-min intervals in the model. Although the modeled peak very closely approximates the observed peak (observed peak flow = 0.0173 m^3/s; simulated peak flow = 0.0174 m^3/s), the response is delayed and the recession limb elongated.

In the ParFlow code, Manning's n values have units of $TL^{-1/3}$, where L = ft and t = s. The final calibrated values for impervious surface in my domain were 1 x 10-2 (m h^{-1}) for pervious areas and 1 x 10-5 (m h^{-1}) for impervious areas. These correspond to the typical values for land covers ranging from pasture – short grass to concrete-lined channels, which characterizes the site well (Chow, 1959).

Comparisons was carried out between the simulated post-GI simulated flows to observed flows using the Manning's n values obtained from the model calibration process. In order to capture the micro-scale changes to grading that directs flows into installed GI facilities, all GI was set the higher Manning's n value of 1 x 10-2, regardless of whether it was a pavement-based facility or a vegetation-based facility. This was done to ensure that flows onto a GI facility were "retained" within the facility. Post GI-Construction monitoring began on June 20, 2015 and continued through April 30, 2016. Several rain events in July, 2015 were selected to compare the model results with monitored data. **Figure 4.12** shows the simulated flows at the pour point compared to the observed flows.

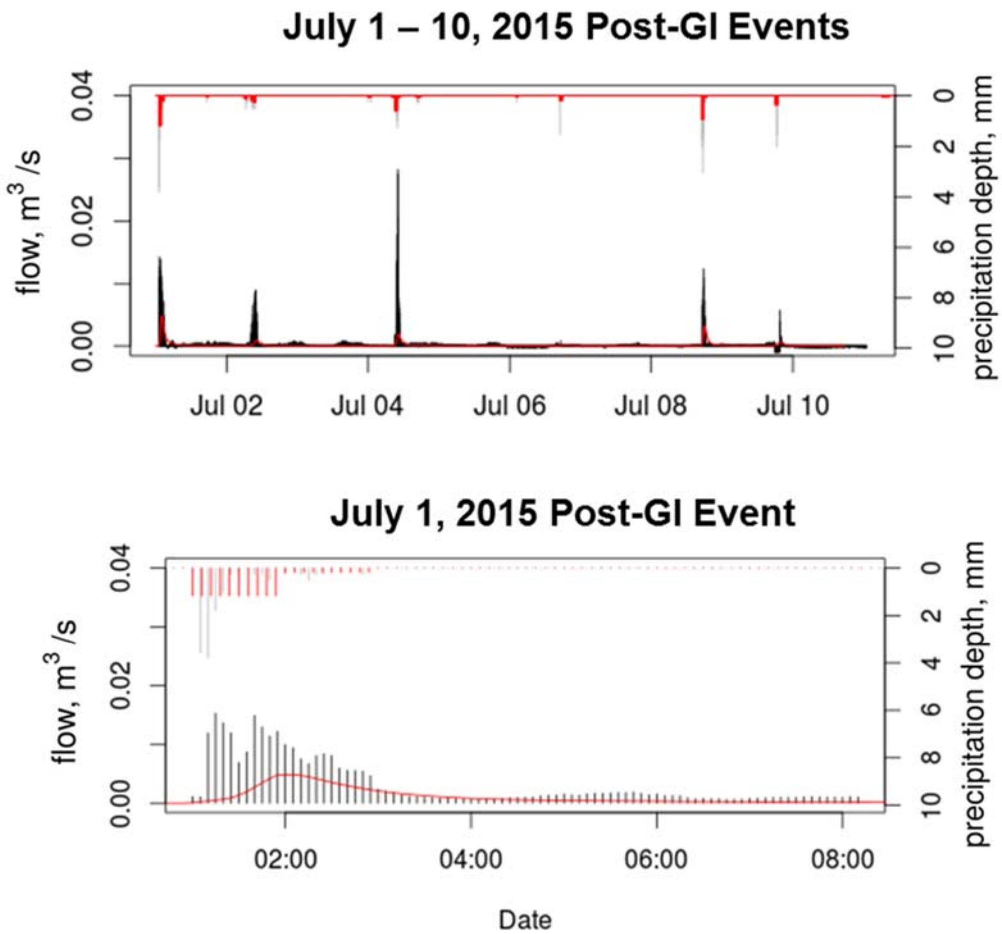


Figure 4.12. Validation of the calibrated model using the post-GI simulation scenario and observed flows.

From the top panel of **Figure 4.12**, we can see that the simulated flow peaks (and total overland volumes) are consistently lower than the observed peaks and overland flow volumes. For example, the July 1, 2015 rain event (total rain depth: 13.5 mm) corresponded with observed cumulative overland flow volumes at the monitoring point of 78.7 m3, and a peak flow rate of 0.0152 cms. The simulated cumulative overland flow volumes at the sewershed's pour point was calculated to be 31.7 m3 (40% of observed), and the peak flow rate was 0.005 cms (32.9% of observed). Ratios between simulated and observed for the validation runs all performed at about this range.

Although this validation is somewhat less than ideal because of the systematic underestimation of overland flow at the pour point compared to the empirical values, two explanations of this outcome gave me enough confidence in the calibrated model's outputs to proceed with scenario testing. First, as can be seen in the precipitation hyetographs in the top panel of **Figure 4.12**, suppressed rainfall intensities from the CLM model may have had some effect on reducing simulated peak flows compared to the observed peak flows. Second, several questions were raised about the quality of the post-monitoring data in the process of model validation. The post-GI flow data provided to DOEE's subconsultant Limnotech from ADS were considerably noisier than the pre-GI data. Despite the period from 2015 – 2016 being a drier precipitation year than 2010 (total annual rainfall in 2015 was 1107.4 mm, or 43.6 inches, and total annual rainfall in 2010 was 1146.048 mm, or 45.12 inches), and the installation of GI in the interim period, statistical analysis of the empirical flows showed no statistical difference in the 99th percentile (peak flows) between the two datasets. The first percentile ("base flows") did show a statistically significant difference, with the post-GI flow data exhibiting higher baseflows. In a closer comparison between two similar rain events, one from August 5, 2010 (total rainfall depth = 29 mm) and one from July 28, 2015 (total depth = 28 mm), pre-GI empirical flows indicated that 3.6% of the rainfall was converted to runoff, while post-GI empirical flows indicated that 19.7% of rainfall was converted to runoff, a counterintuitive result, especially given the amount of GI that was constructed within the sewershed. In contrast, the simulated rainfall – runoff ratio for this event pre-GI was 12.3%, and the simulated rainfall-runoff for the post-GI scenarios ranged from 6% - 7%.

In an email exchange with DOEE's subconsultant Limnotech, it was confirmed that empirical data analysis for a separate control site exhibited significantly higher runoff volumes per inch of runoff in the post-GI monitoring period compared to the pre-GI monitoring period. While not ideal for validation purposes, the order of magnitude reflection of response in the validation runs, coupled with the knowledge that the post-GI empirical flow data are exhibiting systematically *higher* runoff volumes and more noise compared to the pre-GI empirical flow data gave me allowed me to have enough confidence in the model's simulated outputs to proceed with testing spatial configuration scenarios, described in the following chapter.

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CHAPTER 5: TESTING AND MEASURING CATCHMENT-SCALE EFFECTS OF GREEN INFRASTRUCTURE AND IMPERVIOUS SURFACE NETWORKS IN AN URBAN SEWERSHED

INTRODUCTION

While many studies have shown empirical evidence of the hydrological effectiveness of individual GI facilities (eg: rain gardens, bioswales, etc) (Emerson *et al.*, 2005; Davis, 2007, 2008; Li *et al.*, 2009; Driscoll *et al.*, 2015; Page *et al.*, 2015), fewer studies have shown empirical evidence of hydrological effectiveness of networks of GI at the catchment scale. Before-and-after GI installation empirical monitoring of a residential neighborhood in Ohio where residences installed rain gardens have shown weakened correlations between rainfall depths and runoff depths (Shuster and Rhea, 2013). At the regional-scale, an empirical analysis of streamflow patterns in the Maryland region, where many communities have goals of reaching 10%-20% of the landscape to be treated with GI have shown that catchments with GI had less flashy hydrology, lower peak runoff and less frequent flood occurrence, compared to catchments that were untreated (Pennino *et al.*, 2016).

An outstanding question of GI networks is the extent to which the spatial configuration of infiltration opportunities can effect differences in hydrological effectiveness. This is an important question because compared to conventional infrastructure, the spatial configuration of GI depends on spatially distributed processes of redevelopment, property turnover, and voluntary social adoption. Measuring the extent to which specific opportunities for GI should be targeted because of expected differences in hydrological effectiveness should be one factor that cities consider when prioritizing investments at specific sites within catchment areas.

It is impossible to carry out true controlled experimentation in the hydrological sciences. This is because boundary conditions of the site are often dictated by mother nature, or else in modeling, model structure and parameterization of site conditions limit generalization of results (Blöschl, 2017). In this study, the before-and-after GI construction site monitoring data through the RiverSmart Washington project resulted in the evaluation of just one possible spatial configuration of GI, under non-constant meteorological forcing conditions (2010 and 2015). Building a "virtual laboratory" of the site using ParFlow.CLM to test additional spatial configuration scenarios extends the usefulness of the monitoring data, while allowing us to "control for" the effects of boundary conditions on the site. The value from scenario testing is derived from ascertaining the sensitivity of the site to adjustments to the ranges of model parameters and spatial configurations those parameters. As stated above, the purpose of this study is to quantify, under these conditions, the level of variability that can be expected in measured hydrologic response that is associated with different spatial configurations.

SCENARIO DEVELOPMENT AND HYPOTHESES

The model of the base and actual green infrastructure configurations were used to test how spatial configurations of green infrastructure and impervious surfaces affect local hydrology. A total of nine scenarios were tested. Each scenario was simulated using a six-month period of meteorological forcing data (March 1, 2015 – September 1, 2015). This period was chosen for two reasons: first, the availability of rain gage data collected during this time period associated with the post-GI monitoring allowed me to splice in site-specific data to the NLDAS precipitation record when available (see previous chapter); and second, based on the historical rainfall record, the total annual rainfall depth in 2015 (1107.4 mm (43.6 inches)) was the rainfall depth closest to the mean total annual rainfall for the period

1949-2015 (1127.3 mm (44.4 inches)), so 2015 was taken as a relatively representative rainfall year.

All scenarios were run with the same CLM settings and slopes files. This means that the topography of the site and the tree canopy were assumed to be constant across scenarios. All scenarios were initialized with the pressure field output from the equilibrated second spinup stage (see Chapter 4). The spatial configurations of the scenarios are shown in **Figures 5.1 – 5.7**, where yellow designates pervious areas (lawns), gray impervious surface areas (pavements and roofs), light green pavement-type GI (permeable pavement), and dark green vegetation-type GI.

For each scenario, parameters of the surface and subsurface conditions, including distribution of pervious and impervious-assigned Manning's n, porosity and permeability were distributed according the unique surface cover conditions of the scenario. For each scenario, edits to original vector shapefiles for building footprints and the ROW boundaries were made using ESRI software (http://desktop.arcgis.com/en/). Vector polygons representing original building footprints and ROW zones, and building footprints/ROW areas treated with GI were rasterized using GRASS GIS (GRASS Development Team, 2017) in order to keep consistent 5 m gridding and alignment. The base case scenario (**Figure 5.1**), for which spinup was carried out (see previous Chapter) using meteorological forcing data from 2009 until dynamic equilibrium was reached, was also run for the simulation period. This allowed me to compare other scenarios with a comparable case reflecting the site pre-GI construction.

Scenarios were developed to meet the goals of planning and policy considerations and practical implementation and to capture and control for physical variation of the site, in order to best identify specific physical processes causing differences in model output. For example, in order to make a policy-specific recommendation relating to spatial implications of green infrastructure investment, I compare a scenario where all of the public right-of-way (ROW) is retrofit with GI with a scenario where an *equal amount* of private property impervious area (mostly roofs) is retrofit with GI. Because the ROW is on average located in areas of higher flow accumulation in the domain than roof footprints, this scenario comparison tests the effect of spatial configuration of GI while also having a specific policy implication that can inform the location and type of future GI investment. Complete descriptions of all scenarios tested are given in the following sections.

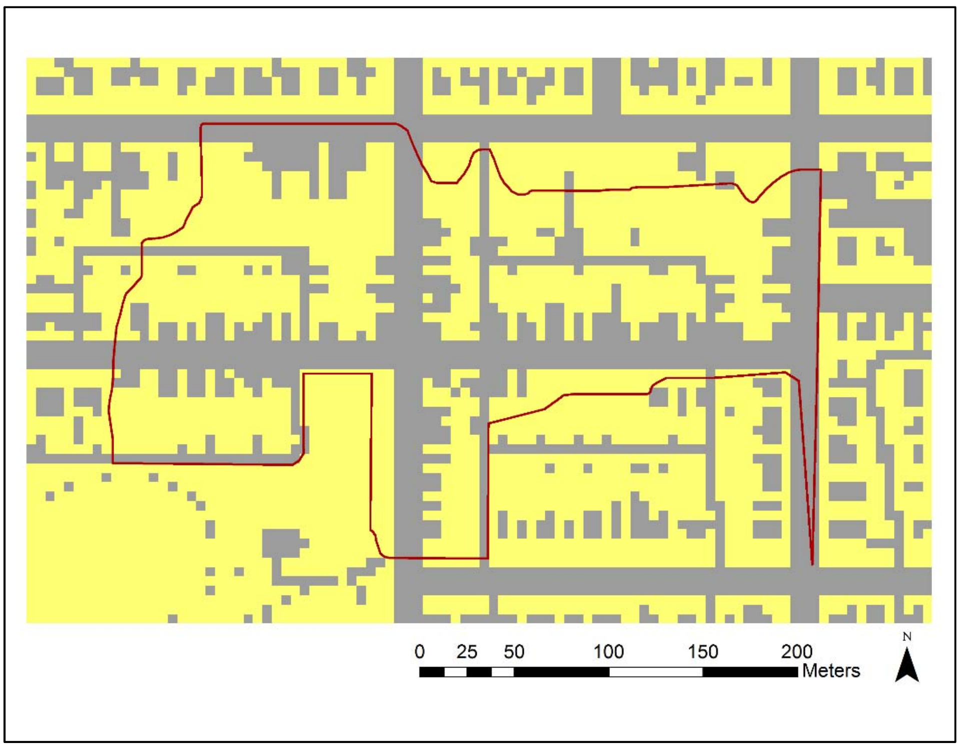


Figure 5.1. Base case scenario land cover used to assign hydraulic conductivity, porosity, and values of Manning's roughness coefficient. Yellow: pervious; Gray: impervious. Red outline: sewershed boundary.

GI Configuration Scenarios

Previous research has suggested that infiltration-based, “run-on” green infrastructure located at sag points, high topographic wetting index, and areas of high flow accumulation may have reduced ability to mitigate overland flows during long, multi-day events (Miles and Band, 2015). Groundwater simulation models have also demonstrated that clustered infiltration-based green infrastructure can result in groundwater mounding, which could reduce storage capacity in prolonged events (Endreny and Collins, 2009; Maimone *et al.*, 2011). On the other hand, other modeling studies have shown extensive infiltration-based BMPs to increase subsurface storage volumes, even beyond pre-development levels (Gobel *et al.*, 2004). Application of the ParFlow modeling system extends these studies to include three-dimensional representation of the subsurface, including the vadose zone, coupled with overland surface flow and land-atmosphere interactions, such as evapotranspiration. The objective of the GI configuration scenarios is to better understand the magnitude of variation that can be attributed spatial configuration and location of GI and the implications of siting. Below I describe the scenarios.

GI2A: ROW

In this scenario (**Figure 5.2**), all of the areas in the public ROW are treated with green infrastructure with properties specified by the pavement-type construction specifications described in the previous chapter. Because GI that treats the ROW treats flows from the surface and does not intercept flows from the subgrade pipe, the pipe, burned in at the centerline is assigned properties of “untreated” impervious surface (Manning’s roughness coefficient, hydraulic conductivity, and porosity).

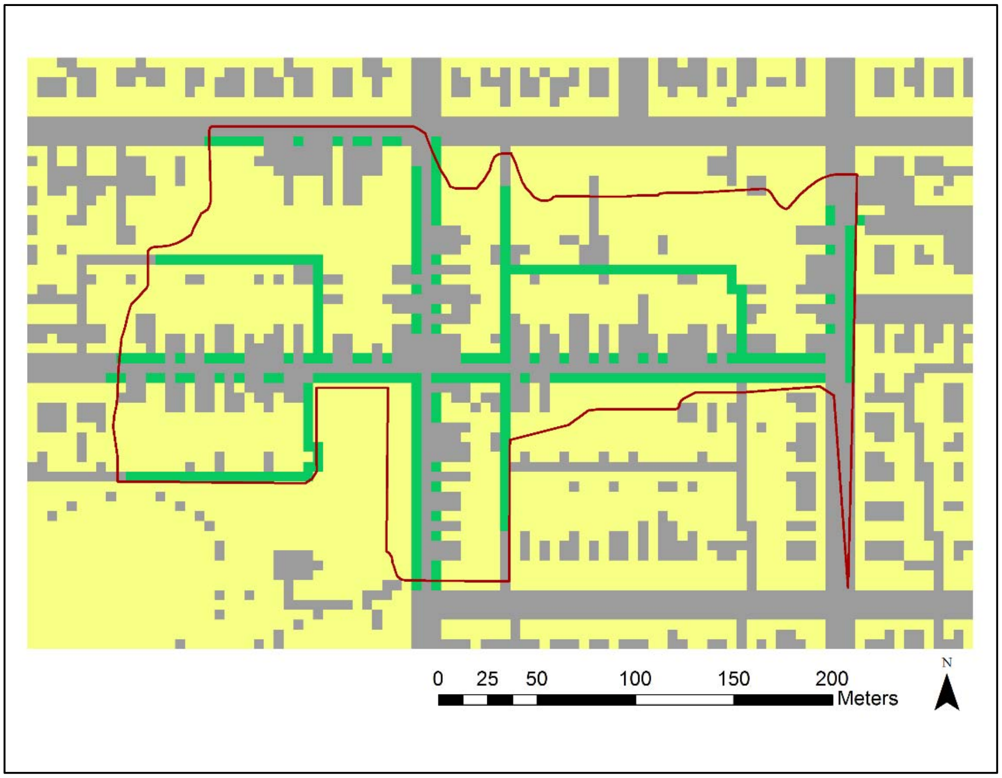


Figure 5.2. GI2A scenario land covers used to assign hydraulic conductivity, porosity, and values of Manning's roughness coefficient. Yellow: pervious; Gray: impervious; Light green: pavement-type green infrastructure. Red outline: sewershed boundary.

GI2B: Roofs

An area equal to the total treated ROW in scenario GI2A is treated at the building footprints in scenario GI2B (**Figure 5.3**). Compared to GI2A retrofits, which correspond at the areas of highest flow accumulation in the sewershed since water is designed to flow towards the storm drain system located in the ROW, GI2B retrofits are spread over higher elevations, and have lower average flow accumulation. The parameters used for the roof retrofits were those specified by the vegetation-type construction specifications described in the previous chapter.

Figure 5.3. GI2B scenario land covers used to assign hydraulic conductivity, porosity, and values of Manning's roughness coefficient. Yellow: pervious; Gray: impervious; Dark green: vegetation-type green infrastructure. Red outline: sewershed boundary.

GI3A and GI3B: Treat low/high accumulation roofs

In these scenarios (**Figures 5.4a and 5.4b**), properties with the lowest/highest mean flow accumulation values (averaged over flow accumulation values for the entire property area) were selected to treat with the vegetation-type GI respectively for GI3A and GI3B. Because properties vary in roof area, there is not a perfect control of area removed between the two scenarios. GI3A treated 4,930 m^2 of impervious surface from the domain, while GI3B treated 4,318 m^2 of impervious surface. These scenarios represent a type of outreach strategy that urban planners and stormwater managers might use to channel additional investment and subsidies towards properties where GI might result in better mitigation of overland flow peaks. Theory suggests that inter-event capacity recovery through infiltration or evapotranspiration will have a large influence on whether retrofitting high flow accumulation properties or retrofitting low-flow accumulation properties will have a bigger effect on peak flow mitigation (Dunne and Black, 1970; Miles, 2014; Miles and Band, 2015).

Figures 5.4A (top), 5.4B (bottom). GI3A (top) and GI3B (bottom) scenario land covers used to assign hydraulic conductivity, porosity, and values of Manning's roughness coefficient. Yellow: pervious; Gray: impervious; Dark green: vegetation-type green infrastructure. Red outline: sewershed boundary.

Impervious Surface Configuration Scenarios

The impervious surface configuration scenarios are designed to bracket the variation expected to result in the local hydrological cycle due to magnitude and spatial configuration of impervious surface area of the site. At the regional watershed scale, previous research has shown that imperviousness located near headwaters results in greater peak flows (Mejía and Moglen, 2010).

IMP1: Disconnect Roofs

The IMP1 scenario (**Figure 5.5**) is identical to the base case scenario for the site, except that the building footprints were not moved to be adjacent to the ROW. Relocating building footprints adjacent to the ROW in the Base case scenario represented the routing of roof runoff to the storm drain collection system. The IMP1 scenario therefore tests the relative impact of simply disconnecting roof downspouts and routing them onto lawns, with no additional amendments to the porosity and storage capacity in the soils (as is done in the GI scenarios).

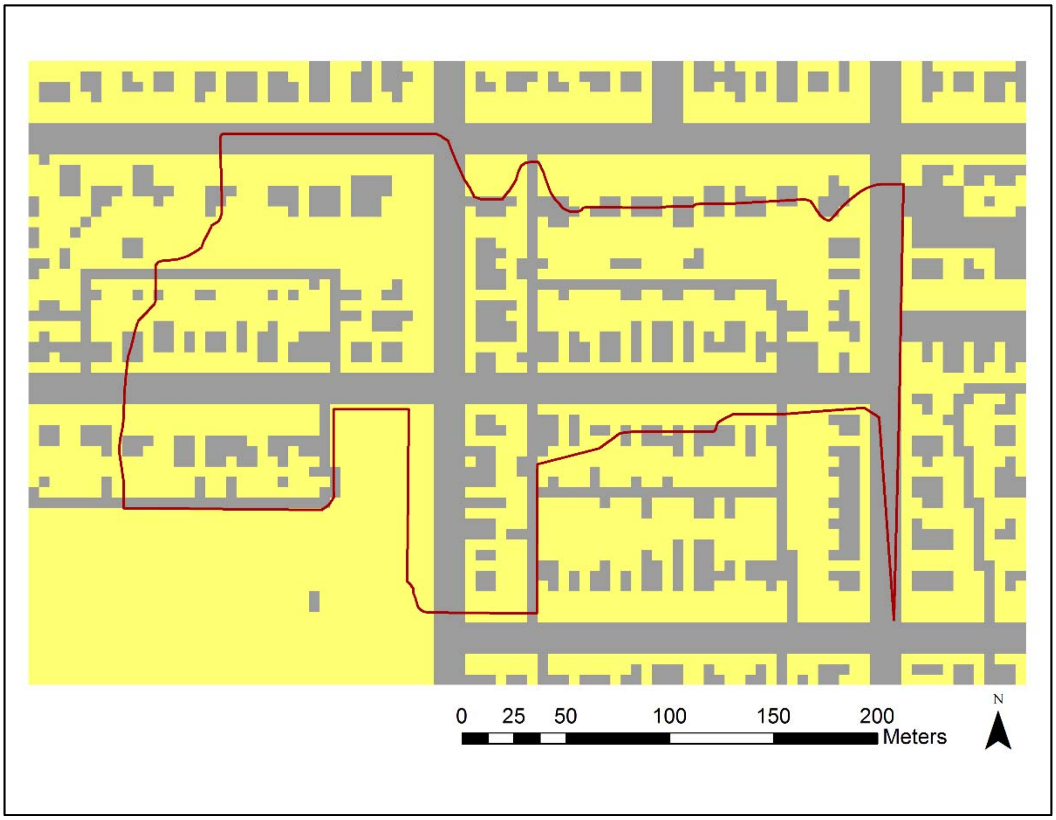


Figure 5.5. IMP1 scenario land cover used to assign hydraulic conductivity, porosity, and values of Manning's roughness coefficient. Yellow: pervious; Gray: impervious. Red outline: sewershed boundary.

IMP2: Redevelopment Pressure to Maximum Zoning and Green Area Ratio Limits

In 2013 The District of Columbia incorporated the "Green Area Ratio" (GAR) into its official zoning regulations. This impervious-surface-area-based rule is meant to set standards to help reduce stormwater runoff and overall environmental quality, by limiting imperviousness and encouraging the use of native vegetation for landscaping. Each zoning classification has been assigned a limitation on the proportion of the site (lot coverage) that can be developed as impervious, in addition to the normal zoning restrictions specifying property line setbacks and floor area ratios in each neighborhood. To construct the IMP2 scenario (**Figure 5.6**), the highest allowable impervious area coverages per the new GAR regulation and previous zoning code was assigned to each parcel within the sewershed. The Lafayette site property values are among the highest in the District, indicating that these is strong redevelopment pressure in this location. In fact, extensions of building footprints occurred within the study period on multiple properties on the site. This scenario represents a future, maximum level of imperviousness on the site that could potentially occur given high redevelopment pressure.

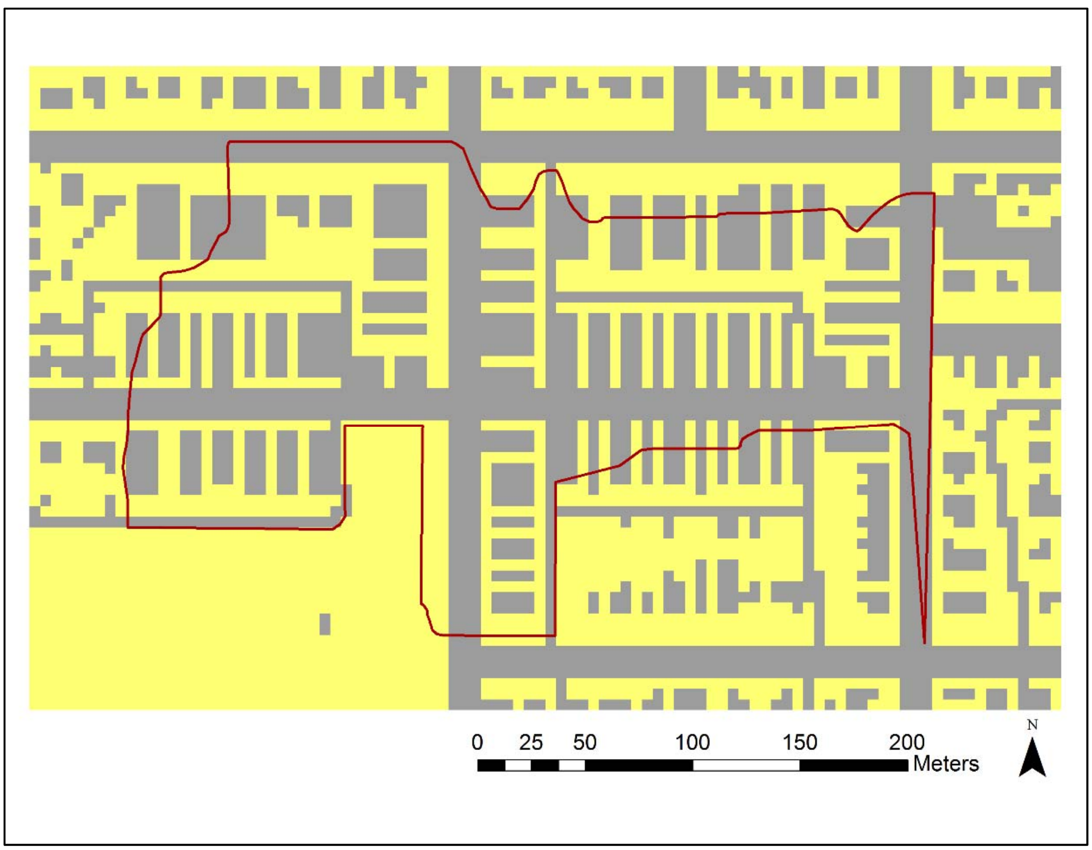
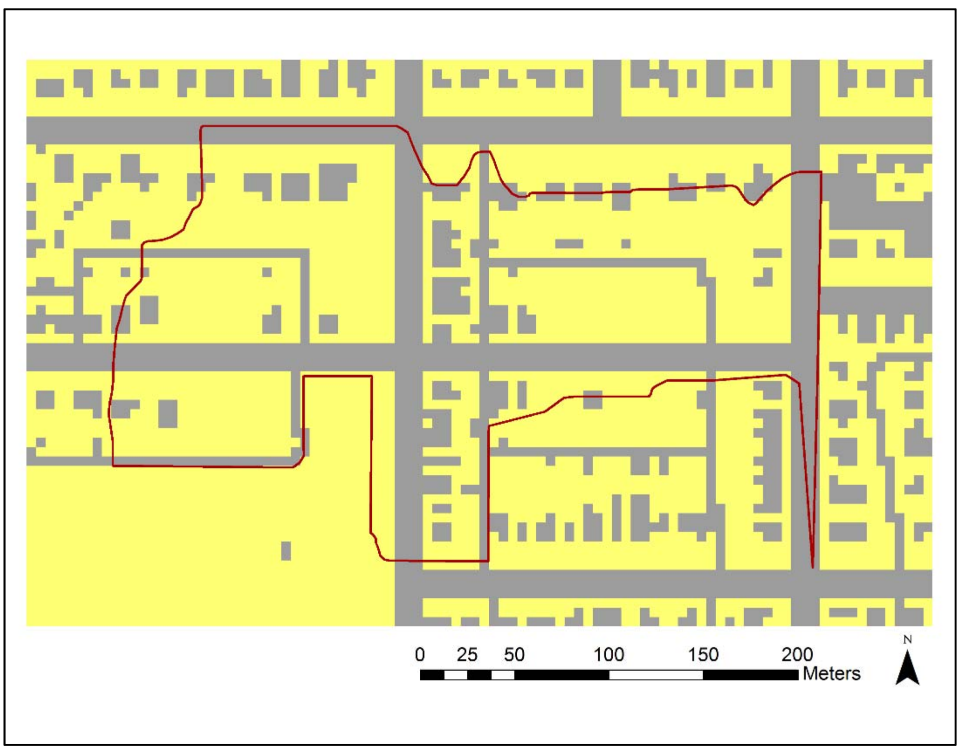


Figure 5.6. IMP2 scenario land cover used to assign hydraulic conductivity, porosity, and values of Manning's roughness coefficient. Yellow: pervious; Gray: impervious. Red outline: sewershed boundary.

IMP3A and IMP3B: Remove impervious areas on low/high flow accumulation properties

The IMP3A and IMP3B scenarios (**Figures 5.7a, 5.7b**) test the impacts of siting impervious surface area relative to topography-determined high and low flow accumulation paths within a drainage area. In the same way used for the GI3A and GI3B scenarios, properties with the lowest (IMP3A) and highest (IMP3B) mean flow accumulation values per property were chosen for impervious surface area removal. Because properties vary in roof area, there is not a perfect control of area removed between the two scenarios. IMP3A removed 4,930 m^2 of impervious surface from the domain, while IMP3B removed 4,318 m^2 of impervious surface from the domain. Comparison of the results of these scenarios are relevant for site planning to minimize runoff peaks, or in the case of shrinking or heavily vacant areas, targeted removal of imperviousness to increase the efficiency of infrastructure remaining on the site.



Figures 5.7a (top), 5.7b (bottom). IMP3A (top) and IMP3B (bottom) scenario land covers used to assign hydraulic conductivity, porosity, and values of Manning's roughness

coefficient. Yellow: pervious; Gray: impervious; Dark green: vegetation-type green infrastructure. Red outline: sewershed boundary.

Comparisons and Hypotheses

The following table **(Table 5.1**) summarizes the comparisons that can be made between scenarios and the decisions that they are intended to help inform.

Table 5.2 summarizes key differences between scenarios and the symbology to be used in the rest of this chapter.

Table 5.1 Scenario comparisons' research questions and policy-relevant context

Scenario Comparisons	Physical performance research question	Planning/policy relevant context
Base vs GI2A/GI2B/GI3A/GI3B	What is the range in variation that can be expected in GI's effect on the local water balance and hydrological response?	Investment in GI construction
GI2A vs GI2B	How do retrofits clustered in the public right of way compare to retrofits dispersed on private property in effect on the local water balance and hydrological response?	Investment in GI construction in the public right of way compared to investment in GI construction on private properties Development of metrics that incorporate physical effects, investment, and community benefits
GI3A vs GI3B	What is the range in variation in local water balance and hydrological response associated with spatial location and configuration of GI retrofits on private properties?	Targeted outreach and subsidization of GI construction on private properties
GI3A vs IMP3A GI3B vs IMP3B	How does the effect of limiting imperviousness differ from the effect of treatment of imperviousness using GI on the local water balance and hydrological response?	Targeting impervious surface removal (for example, in high vacancy neighborhoods, or on public land) and investment in green infrastructure Spatial decision-making in new development or redevelopment, development of zoning and parcel-level new development regulations
Base vs IMP1 vs GI2B	How does downspout disconnection compare to roof runoff treatment with rain gardens in effects on local water balance	Marginal benefits of downspout disconnection and treatment of private roof runoff investments

Base vs IMP1 vs IMP2	What is the range in variation in effect on the local water balance and hydrological response associated with connectivity of impervious surface area, and increased surface area?	Anticipation of effects of re-development pressure and increasing building footprint size on private properties on infrastructure performance Development of vegetation/impervious surface based requirements for parcel-level redevelopment
IMP3A vs IMP3B	How does limiting imperviousness in different spatial configurations affect local water balance and hydrological response?	Targeting impervious surface removal (for example, in high vacancy neighborhoods, or on public land)

Table 5.2 Scenario summaries

	Impervious (m²)	Pervious, non-GI (m²)	Vegetated GI (m²)	Pavement GI (m²)	Percent Impervious	Percent Impervious Treated*
Base	23375	29450	0	0	44%	NA
GI2A	15875	29450	0	7500	30%	14%
GI2B	15150	29450	8225	0	29%	16%
GI3A	19500	29450	3875	0	37%	7.3%
GI3B	19025	29450	4350	0	36%	9.2%
IMP1	23850	28975	0	0	45%	NA
IMP2	31900	20925	0	0	60%	NA
IMP3A	19325	33500	0	0	37%	7.3%
IMP3B	20100	32725	0	0	38%	9.2%

* Compared to Base

Scenario Code	Description	Plot Colors
Base	No treatment with GI; All roofs connected via downspout	Gray/black
GI2A	All impervious area in ROW treated with permeable pavement GI; roofs connected via downspout	Orange
GI2B	Equal roof area as GI2A treated with vegetative GI	Brown
GI3A	Roofs located on low flow accumulation properties treated with GI	Blue
GI3B	Roofs located on high flow accumulation properties treated with GI	Purple
IMP1	All roofs disconnected from storm drain in ROW	Red
IMP2	Maximum imperviousness on every property	Black-dashed
IMP3A	Roofs located on low flow accumulation properties removed and replaced with native soil properties	Light Green
IMP3B	Roofs located on high flow accumulation properties removed and replaced with native soil properties	Dark Green

The concept of limited “capacitance” of urban watersheds (Miles and Band, 2016) indicates that the more limited a watershed’s capacitance, the more sensitive it is likely to be to spatial configurations of run-on infiltration opportunities. Therefore, I hypothesized that during multi-day events and high total rainfall depth events (wetter conditions), treatments (either with GI or removal of imperviousness) located in high flow accumulation areas would become less effective due to slower ability to recover capacity.

I hypothesized that less intensive treatments, such as roof disconnection, and mere removal of imperviousness, without increasing hydraulic conductivity of receiving native soils would have more limited effects than increasing hydraulic conductivity through GI retrofits.

Research has shown that impacts to both the hydrological regime and ecological impacts can be observed at impervious thresholds as low as 2-3% for watersheds (Booth and Jackson, 1997; King *et al.*, 2011), however based on a meta-analysis of impervious cover-based metrics, the average level of imperviousness at which impacts to stream flow were detected was 7% (Schueler *et al.*, 2009). The summarization of these research findings into the “10 percent rule” has been an important and memorable metric for watershed planners (Randolph, 2004; Daniels, 2014). Therefore, I hypothesized that the difference in performance between GI2A and GI2B, paired spatial scenarios that treated over 10% of the site’s impervious surface, will be more apparent than the differences in performance between GI3A and GI3B and IMP3A and IMP3B, which only treated about 7-9% of impervious surfaces. In urban sewersheds, 15% retrofits of impervious surface with green infrastructure has been cited as a threshold above which there will be detectable differences in pipe flows (Crockett, 2015). Using the monitoring data collected by Limnotech and the DOEE as representative of the amount of noise present in the site flows, I hypothesized that only performance comparisons between scenarios where differences in imperviousness exceed 15% will exceed the of variation in monitored overland flow. Paired scenarios that have differences in imperviousness over 15% include: Base/GI2A, IMP2/Base, IMP2/GI2A, IMP2/GI2B, IMP2/IMP1, IMP2/IMP3A, IMP2/IMP2B.

RESULTS

Overland Flow

Overland flow was calculated at the pour point of the sewershed (the point which all flows drain past, in this case, the monitoring point) for each of the scenarios for the simulation period. The method for calculating overland flow at any point within the domain is based on Manning's equation:

$$Q = VA = \left(\frac{1.00}{n}\right) AR^{\frac{2}{3}} \sqrt{S}$$

where Q is volumetric flowrate (L^3T^{-1}), V is flow velocity (LT^{-1}), A is cross-sectional area (L^2), n is Manning's roughness coefficient (calibrated for the impervious land cover type as explained in the previous chapter $TL^{-1/3}$)), R is the hydraulic radius (L), and S is bed slope. Within ParFlow, Manning's equation (above) is adapted to use pressure head calculated at any surface grid cell, so that the equation for overland flow at that point as below:

$$Q = \left(\frac{dx}{n}\right) P^{\frac{5}{3}} \sqrt{S}$$

where dx (L) is the horizontal resolution of the domain, and P is the pressure head (L) output from the three dimensional array at the time t at the location of the grid cell. The ParFlow application of Manning's equation assumes that for wide channels, the hydraulic radius can be replaced by depth, which is equivalent to pressure head (Maxwell *et al.*, 2016). The grid cell that was chosen to calculate overland flow was the outlet of the sewershed, where flow monitoring was carried out, pre- and post-installation of GI, also referred to the sewershed's "pour point". All overland flow from the sewershed flow passed this point, therefore overland flow at this point is an integrated measure of flow heterogeneity within the sewershed. Overland flow was calculated for the entire simulation period for all nine scenarios.

10-day simulation window hydrographs

Figure 5.8 shows an example period of calculated overland flow measured at the sewershed's pour point, and **Figure 5.9** shows the context of the four rainfall events in this 10-day window within the context of the simulated period.

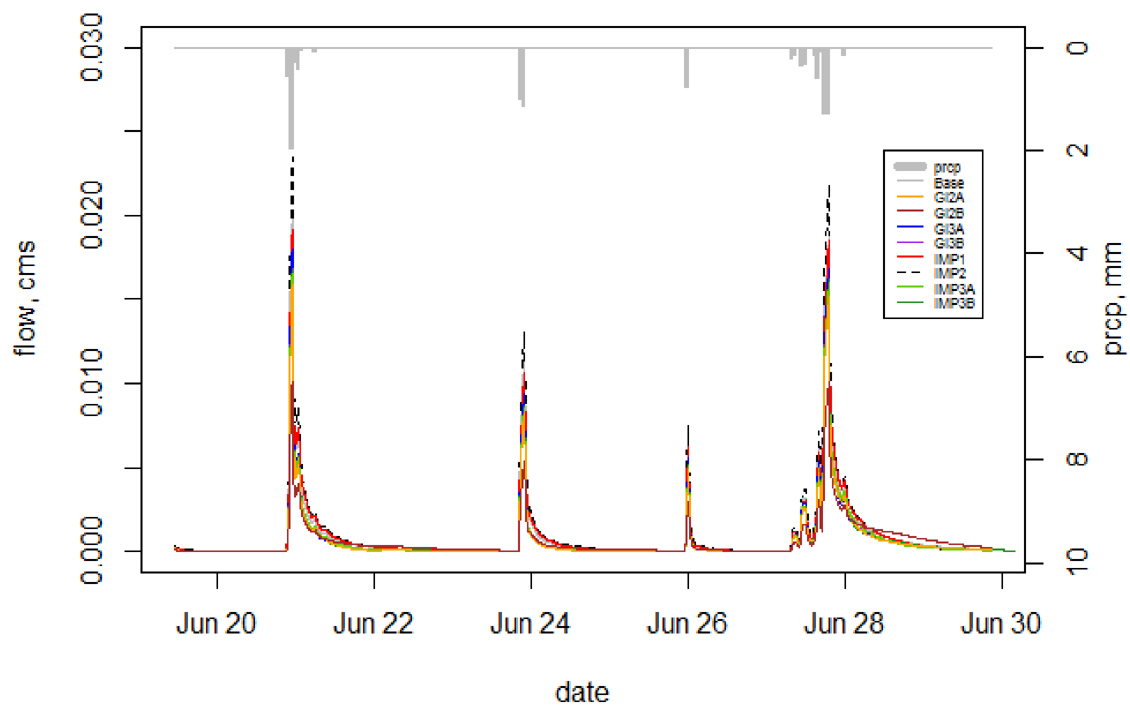


Figure 5.8. Overland flow at pour point hydrographs for all nine scenarios. The 10-day period shown here (June 20, 2015 through June 30, 2015) included four rainfall events, separated by inter-event dry periods of at least one day. The total depths for each of the events were 34.0 mm (1.34 in), 21.6 mm (0.85 in), 7.6 mm (0.30 in), and 47.0 mm (1.85

in). This 10-day period represented the period within the run window with the most frequent and largest intensity rainfall events.

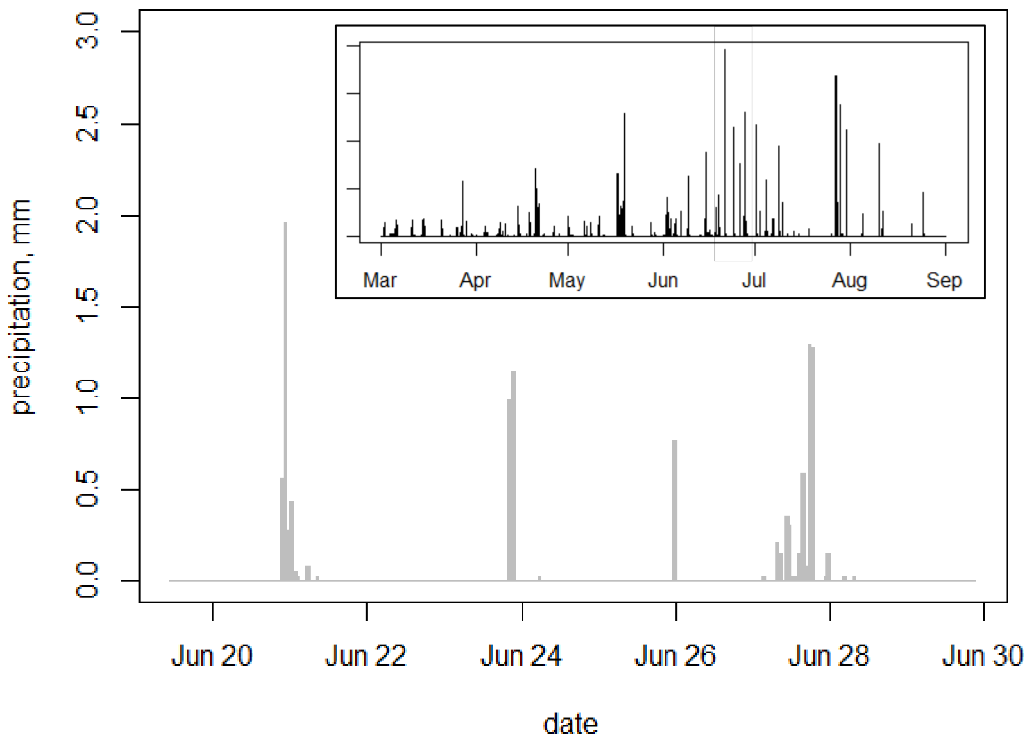


Figure 5.9. Precipitation records for June 20, 2015 – June 30, 2015. Inset shows the selected window for overland flow examination in the context of the entire simulation period, from March 1, 2015 – September 1, 2015. This window includes the highest-intensity rainfall event as well as the wettest 10-day period.

To better differentiate the overland flow patterns of the scenarios, two measures of effect on overland flow were chosen for closer examination: the total volume of runoff resulting from an event, and the peak flow of the event. From an infrastructure management perspective, lower overall volumes reaching the pourpoint and lower peak flows are both desirable outcomes. This may differ from urban stream restoration goals that may seek to restore pre-development baseflows while mitigating flashiness (storm runoff peaks). From an infrastructure-centric perspective, infrastructure managers are typically trying to reducing loading on centralized drainage infrastructures, especially those that are shared with domestic wastewater conveyance. The measures and rankings for each scenario were calculated (**Table 5.3**). A visualization of changes in ranking between events is shown in **Figure 5.10**.

A comparison of the overall 10-day rankings shows that IMP2 (maximum allowable imperviousness per-parcel for every parcel) had the highest magnitude values for both max peak flow over the 10-day period and for total volume of runoff over the 10-day period. The max peak flow for IMP2 (0.023 cms) is 13% greater than the max peak flows for Base (0.020 cms) and 17% greater than the IMP1 (disconnected scenario). When comparing peak flows, disconnecting roofs from ROW "pipe" decreased the max peak flow by 5%, compared to Base. However, this decrease in max peak was evident only in the first rain event in this 10-day window. In the third rain event, the peak flow from IMP1 even marginally exceeded the peak flow from Base. This suggests that the mere disconnection of rooftop imperviousness with no provision of additional storage in the receiving lawn area may do little to mitigate flow peaks during multiday events, after the initial soil storage is exhausted. A comparison between total runoff volumes between Base and IMP1 even show that disconnected roofs resulted in about 4% *more* total runoff volume than Base, suggesting that additional volume capture is necessary (for example through rain barrels or rain gardens) in order for downspout disconnection to have the desired effect on flow mitigation. However, when the flow duration curves are examined (following section), this difference appears to be negligible.

Table 5.3 Scenario rankings for peak flows and total event volumes for four consecutive events in 10-day window

Peak Flows

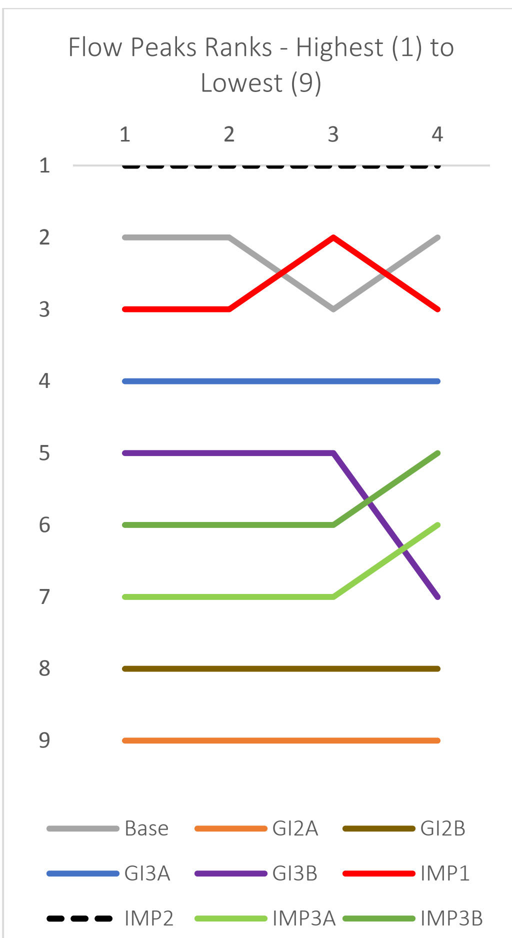
	Event 1		Event 2		Event 3		Event 4		10-day max	
	cms	**rank**	**cms**	**rank**	**cms**	**rank**	**cms**	**rank**	**cms**	**rank**
Base	0.020	2	0.011	2	0.006	3	0.019	2	0.020	2
GI2A	0.010	9	0.005	9	0.003	9	0.010	9	0.010	9
GI2B	0.016	8	0.008	8	0.005	8	0.015	8	0.016	8
GI3A	0.018	4	0.009	4	0.006	4	0.017	4	0.018	4
GI3B	0.017	5	0.009	5	0.005	5	0.016	7	0.017	5
IMP1	0.019	3	0.011	3	0.006	2	0.019	3	0.019	3
IMP2	0.023	1	0.013	1	0.007	1	0.022	1	0.023	1
IMP3A	0.017	7	0.009	7	0.005	7	0.016	6	0.017	7
IMP3B	0.017	6	0.009	6	0.005	6	0.016	5	0.017	6

Total Runoff Volumes

	Event 1		Event 2		Event 3		Event 4		10-day total	
	m^3	**rank**	**m^3**	**rank**	**m^3**	**rank**	**m^3**	**rank**	**m^3**	**rank**
Base	2154	3	1188	3	303	3	3572	3	7217	3
GI2A	1368	9	789	7	191	8	2610	9	4957	9
GI2B	1505	8	717	9	190	9	2830	8	5243	8
GI3A	1669	4	802	4	222	4	3028	5	5721	4
GI3B	1629	6	796	5	211	6	2989	6	5624	6
IMP1	2298	2	1221	2	320	2	3699	2	7539	2
IMP2	2660	1	1429	1	390	1	4078	1	8557	1
IMP3A	1668	5	762	8	206	7	3047	4	5683	5
IMP3B	1615	7	796	6	212	5	2986	7	5608	7

Figure 5.10 visualizes all changes in rankings in flow peak and total volume magnitudes that occur over the 10-day analysis period. Crossovers in rankings between paired spatial configuration scenarios (i.e., when total treated areas are held constant and only spatial configuration or location of the intervention is changed. For example, the pair GI2A and GI2B) across events indicates context-dependent differences in hydrological behavior. Comparing paired scenarios' peak flow rankings, the only crossover between a paired spatial configuration scenarios' rankings occurs between Base and IMP1. Other paired

scenarios GI2A and GI2B, GI3A and GI3B and IMP3A and IMP3B all maintain consistent relative rankings: GI2A (downslope impervious treated) has lower flow peaks than GI2B (upslope roofs treated) in all four events; GI3B (downslope roofs treated) has lower flow peaks than GI3A (upslope impervious treated) in all four events, and IMP3A (upslope impervious removed) has lower flow peaks than IMP3B (downslope impervious removed) in all four events. However, as can be seen from **Table 5.3**, the differences in magnitude between peaks between Base and IMP1 and IMP3A and IMP3B are negligible (less than 1%). This indicates that spatial configuration of imperviousness when no additional storage volume is provided has limited effect on peak flow mitigation.



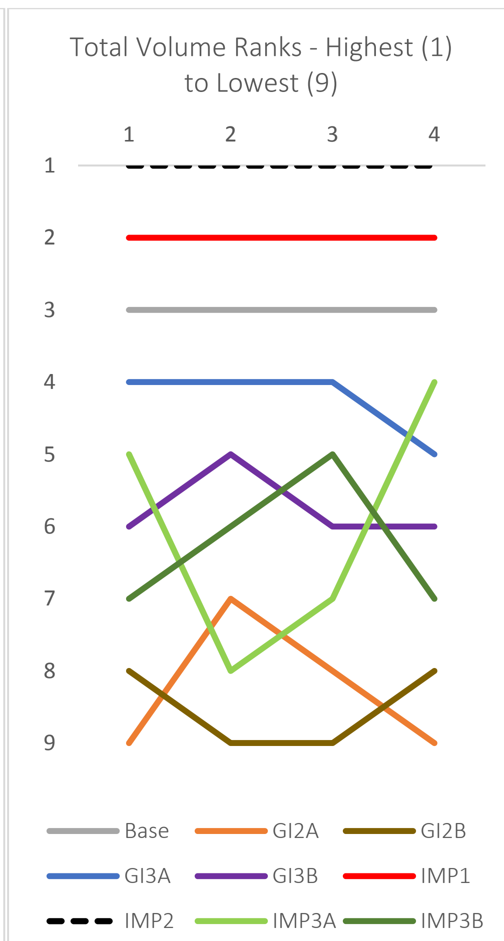


Figure 5.10 Comparisons of magnitude rankings for flow peaks (left), and event runoff volumes (right), between nine simulated scenarios, over four rainfall events in a 10-day window.

In contrast, differences in spatial configuration in placement of GI treatment areas (GI2A vs GI2B and GI3A vs GI3B) were as high as 40%. Larger differences in attributed to spatial configuration were observed between the GI2A and GI2B scenarios, which had 14.2% and 15.6% of the area within the sewershed treated with GI, respectively. GI3A and GI3B had smaller proportions of their total contributing area retrofit with GI (7.3% and 8.2%, respectively), about half of the total treated area in GI2A and GI2B scenarios. This result implies that differences in peak flow mitigation associated with spatial configuration and placement of GI become more apparent as the total area treated with GI increases. In Miles (2014), no differences in streamflow were found when upslope versus downslope roofs in a low-medium density neighborhood were treated with GI. In that study, residential rooftops comprised only about 7% of the total watershed area, compared to about 15% in this study.

While peak flows were lower for the disconnected roof scenario (IMP1) compared to Base in three out of four rain events, Base had lower total volumes of runoff compared to IMP1 in all four rain events. The increased volume of total runoff in each event for IMP1 ranged between 2.5% and 6.6% higher than the volume of total runoff for the Base scenario. GI3A's total volume of runoff was slightly higher than GI3B's total volume of runoff in each rainfall event (ranging between 0% - 5% larger volumes), indicating that although there was little difference between these scenarios' peak flows, there was more of a difference in the ultimate fates of rainfall between these two scenarios. Total runoff volumes for each event exhibited several rank crossovers between paired spatial configuration scenarios

(**Figure 5.10**). During the first rainfall event (34mm) GI2A (downslope ROW treated) reduced total runoff volumes more than GI2B (upslope roofs treated), and IMP3B (downslope impervious removed) reduced total runoff volumes more than IMP3A (upslope impervious removed). Both these comparisons provide evidence that spatial configuration of GI and imperviousness matter: when run-on opportunities and storage areas are located in more downslope areas, more runoff volume is intercepted. However, after the first event, during the second (21 mm) and third (7.6 mm) events (perhaps before downslope capacity has been recovered), the scenarios that provide upslope infiltration and storage opportunities mitigate more total volumes than the scenarios that provide downslope infiltration and storage opportunities. After these two smaller events, capacity is "recovered" in downslope areas, and maximum infiltration opportunities in the downslope configurations again realizes its advantage in intercepting more subsurface flow during the fourth event (1.85 mm).

Flow Duration Curves

Flow duration curves (FDCs) are a way visually compare entire distribution profiles of a time series of flows. They show the amount of time that a given flow will be exceeded.

Figure 5.11 shows the flow duration curves of the simulated scenarios compared to each other, and compared to observed empirical flows measured within the pipe. As was explained in the previous chapter, empirical flows pre-GI construction were collected from 2010-07-14 to 2010-12-15, and empirical flows post-GI construction were collected from 2015-06-20 to 2016-04-30. From **Figure 5.11** several high-level trends are apparent. First, all scenarios exhibit larger "base flows" than what is observed from the monitoring data. This includes the simulated base, which had equal levels of imperviousness with connected roofs as the empirical base case, and the simulated IMP1 and IMP2, which had equal, and higher levels of imperviousness with disconnected roofs, respectively. Both the empirical Base and empirical GI flows do not exhibit many intermediary flows; from a very low flow condition, the FDCs jump up to higher flow conditions about 10% of the time. This pattern could be attributed to either lack of sensor sensitivity to low flows or to the model's overestimation of base flows from the site. Issues with empirical data are addressed in greater detail in a later section.

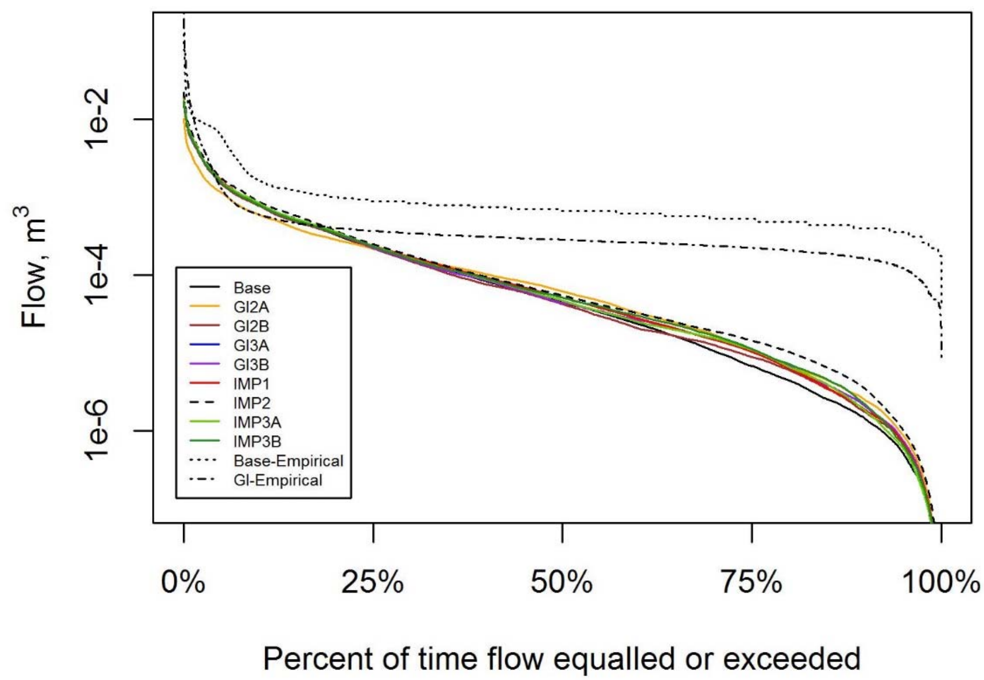
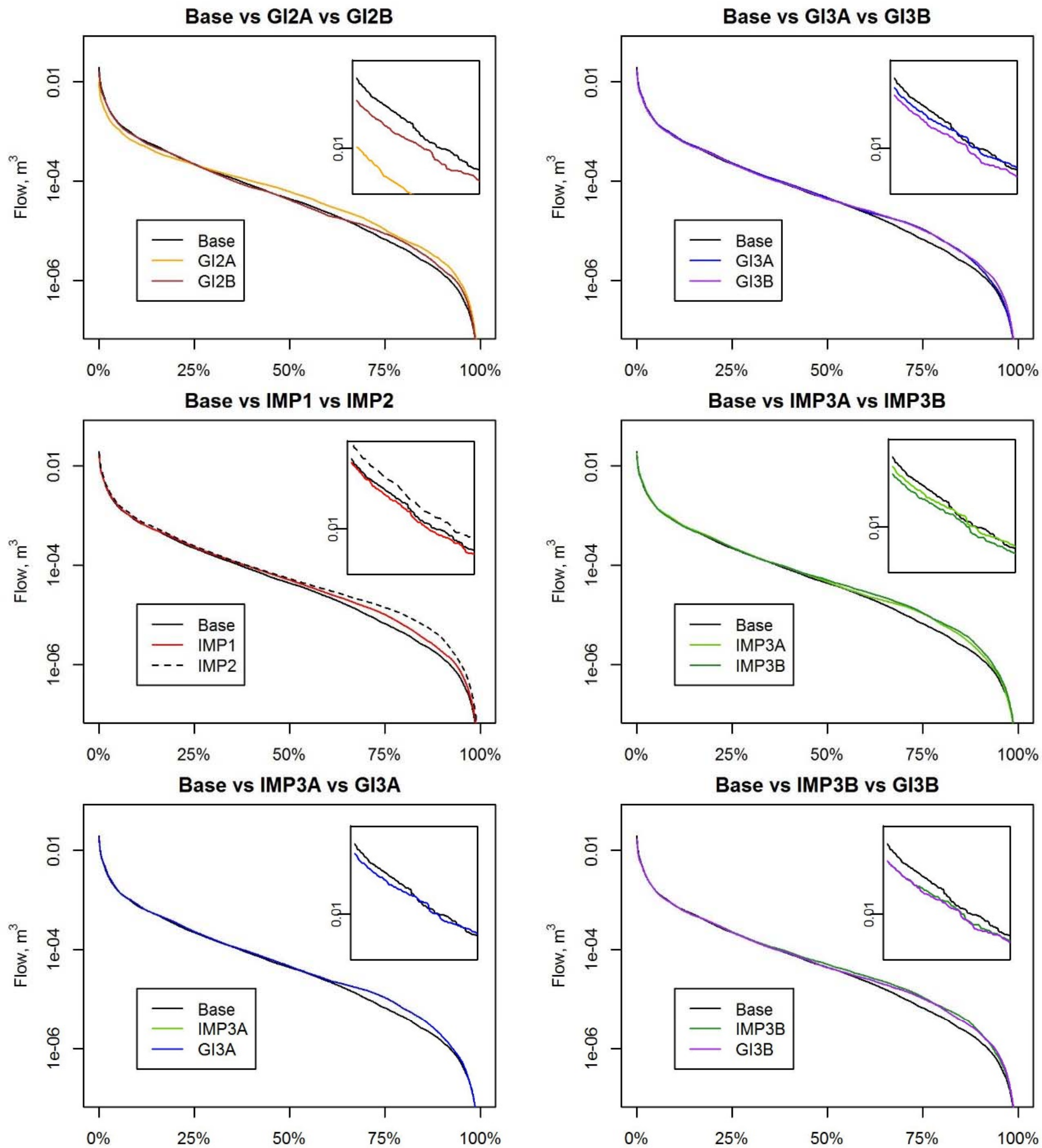


Figure 5.11 Flow Duration Curves of simulated scenarios and empirical observed pipe flows

Although simulated low flows are larger than empirical flows, **Figure 5.11** shows relatively good agreement between the top 15% of flows between the simulated and empirical data. However, the FDCs show the distribution in peak flows to be underestimated by the model. This is not a completely apples-to-apples comparison however, since the rainfall total depth and intensity profiles for the empirical data and the simulation period also differ. Differences in the magnitudes of event-based precipitation are discussed further in the following section.

FDCs comparing scenarios are shown in **Figure 5.12.** Comparisons of the full distribution of flows, as well as zoomed-in insets of the maximum 1% of flows for each of the scenarios are depicted. A qualitative evaluation of the FDCs shows that among spatial configuration paired scenarios the greatest variation was observed between paired scenarios GI2A and GI2B. GI3A/GI3B and IMP3A/IMP3B exhibited very small differences, both with the high flow accumulation properties treated (GI3B and IMP3B) scenarios with lowered peak flows. The small differences in peaks cannot be clearly attributed to spatial configuration however, because the property-specific conditions of the site did not result in perfectly equal treated/removed areas between the 3A and 3B scenarios; the 3B scenarios had slightly higher amounts of impervious area treated/removed (**Table 5.2**). The least variation was observed between GI3A and IMP3A, and GI3B and IMP3B. These comparisons compare the effects of increasing hydraulic conductivity by 1 – 6 orders of magnitude in the top four layers of the domain. In order to control for the small differences in areas treated with GI between the GI3A/IMP3A and GI3A/3B cases, event-based analyses that normalized by the total areas treated/removed were performed.

The FDCs show that the only scenario to have a maximum peak flow clearly above that of the Base case is IMP2, the scenario that has 36.5% more impervious surface area than the Base case. Treatment of the ROW shows decreased low flow frequencies compared to Base in addition to decreased peak flows, indicating some evidence of a losing" stream type response from the burned in pipe to the surrounding soil.



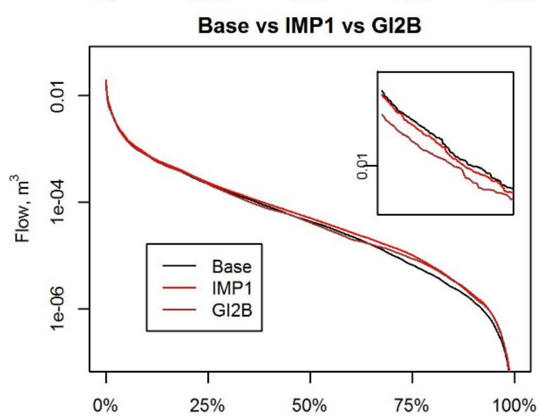


Figure 5.12 FDC (flow duration curves) comparisons among key scenarios.

Event-Based Analysis

A script was written in R to isolate the peaks and total rainfall volumes associated with each rainfall event from the simulated overland flow and monitored pre and post-GI time series. While FDCs allow for comparisons of entire distributions of flows, event-based analysis allows for an examination of the contexts of specific runoff behaviors. Runoff behaviors can vary depending on the size and intensity of the rainfall event, as well as the pre-event wetness or inter-event period. According to theory, a watershed that is highly sensitive to pre-event wetness would be expected to infiltrate less runoff when inter-event periods are short (and the watershed has less time to recover storage capacity) than a watershed that is less sensitive to pre-event wetness. Similarly, if a watershed is capacity-limited, then we would expect GI in low-lying, high flow accumulation locations in the watershed to perform less effectively than GI in upland areas which would be expected to recover capacity more quickly. If, on the other hand, a watershed has high capacitance (Miles and Band, 2015), then perhaps GI in low-lying, high-flow-accumulation locations in the watershed would perform more effectively than GI in upland areas, since in addition to their direct contributing areas, they would intercept other upland areas' flows.

Rainfall events were identified based on inter-event dry periods of at least 10 hours. If rainfall stopped, but started again in less than 10 hours, both periods are counted as part of the same rainfall 'event.' All overland flow (as measured from the pour point) until flows returned back to zero were summed for a total event volume of runoff. Each event's maximum flow peak was also calculated.

Total volumes mitigated by GI retrofits and impervious surface removed were calculated by subtracting the total event-based runoff volumes from each of the alternative scenarios from the total event-based runoff volumes from the Base case. In addition, since the paired spatial configuration scenarios included slightly different totals of impervious surface retrofit, per-m^2 volumes intercepted for each event were calculated based on the total treated/removed area of impervious surface for the scenario. This was a way of assessing per-m^2 efficacy of the GI retrofits. **Equation 5.1** summarizes the calculation:

$$E_{S_{i,j}} = \frac{\int_i^j (Q_{Base} - Q_S)\ dt}{A_S} \qquad [5.1]$$

where $E_{S_{i,j}}$ is the area-normalized efficacy [L] of scenario *S* for the event defined by *(i,j)*; Q_{Base} is the flow rate for the Base case scenario [L^3T^{-1}]; Q_S is the flow rate for scenario *S*; A_S is the total area of [L^2] treated/removed impervious surface in scenario *S*; $(i, j) \in \{(i_1, j_1), (i_2, j_2) \ldots (i_n, j_n)\}$ are paired times marking the start and end of events 1…*n* for *n* is total number of rain events; and $S \in \{GI2A, GI2B, GI3A, GI3B, IMP3A, IMP3B\}$ is a paired spatial configuration scenario. The area-normalized efficacy $E_{S_{i,j}}$ for each defined event can also be understood as the average mitigated depth of rainfall per square meter of GI. Plots of $E_{S_{i,j}}$ by the event total rainfall depths are shown in **Figure 5.13.** Steeper slopes indicate that the treatment/removal of imperviousness is able to intercept more runoff compared to the Base scenario (more effective). On average, no significant differences associated with spatial configuration are observed treated or removed rooftop imperviousness. There is an observable difference between the performance of GI2A and GI2B however, with each m^2 of GI in the GI2A case intercepting more runoff on average than the GI2B case.

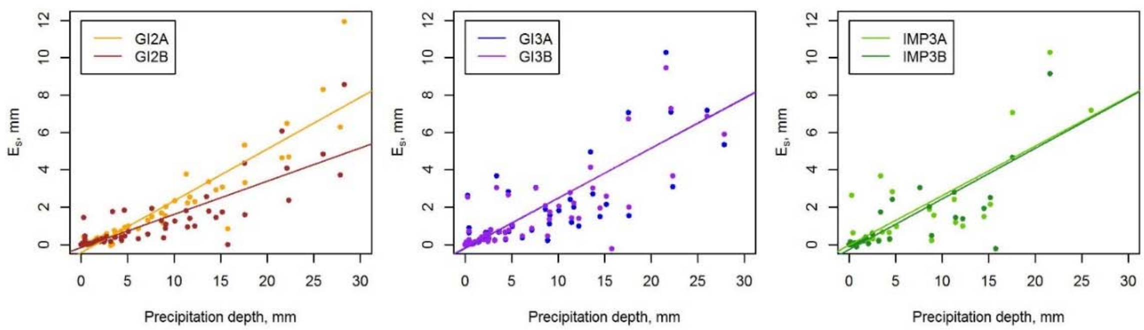


Figure 5.13. Calculated efficacy (E_s) of treatment per square meter of treated/removed impervious area.

Assuming the runoff outputs for each scenario are representative for that particular configuration of spatially distributed parameters, there is a particular interest in explaining the circumstances under which paired spatial configuration scenarios' E values sometimes reverse themselves. For example, out of 72 identified rainfall events, $E_{GI2A} > E_{GI2B}$ for 48 events, while $E_{GI2B} > E_{GI2A}$ for 24 events; out of 72 identified rainfall events $E_{GI3B} > E_{GI3A}$ for 32 events, while $E_{GI2B} > E_{GI2A}$ for 40 events; and out of 45 identified rainfall events, $E_{IMP3B} > E_{IMP3A}$ for 12 events. In order to more closely examine if there was statistical evidence that either total event rainfall depth or the inter-event period influenced whether the upslope or downslope spatial configuration was more effective in reducing the rainfall-runoff ratio, an additional analysis was performed. Events where the spatial configuration treating or removing imperviousness on upslope (low flow accumulation) properties performed better (higher E) than the spatial configuration treating or removing imperviousness on downslope (high flow accumulation) properties were defined as the function *g* **(Equation 5.2**)*:*

$$g(x_{i,j})\begin{cases}0 & x_{i,j} \in \{E_{up,i,j} > E_{down,i,j}\} \\ 1 & x_{i,j} \in \{E_{down,i,j} > E_{up,i,j}\}\end{cases} \quad [5.2]$$

where $x_{i,j}$ is the rainfall event defined by start time *i* and end time *j*; $E_{\{up,down\},i,j}$ are the E values calculated in **Equation 5.1;** and "up" scenarios include GI2B, GI3A, and IMP3B and "down" scenarios include GI2A, GI3B, and IMP3B. The $g(x_{i,j})$ binary state classification was then used as a classification state to group types of event conditions according to total rainfall depth and inter-event period. If the state classification is independent of these conditions then the state assignment should be random with respect to the condition. If on the other hand, the state classification is shown to be dependent on these conditions, then a comparison of the condition means between the two states can reveal a causal explanation for higher or lower efficacy *E* of the intervention.

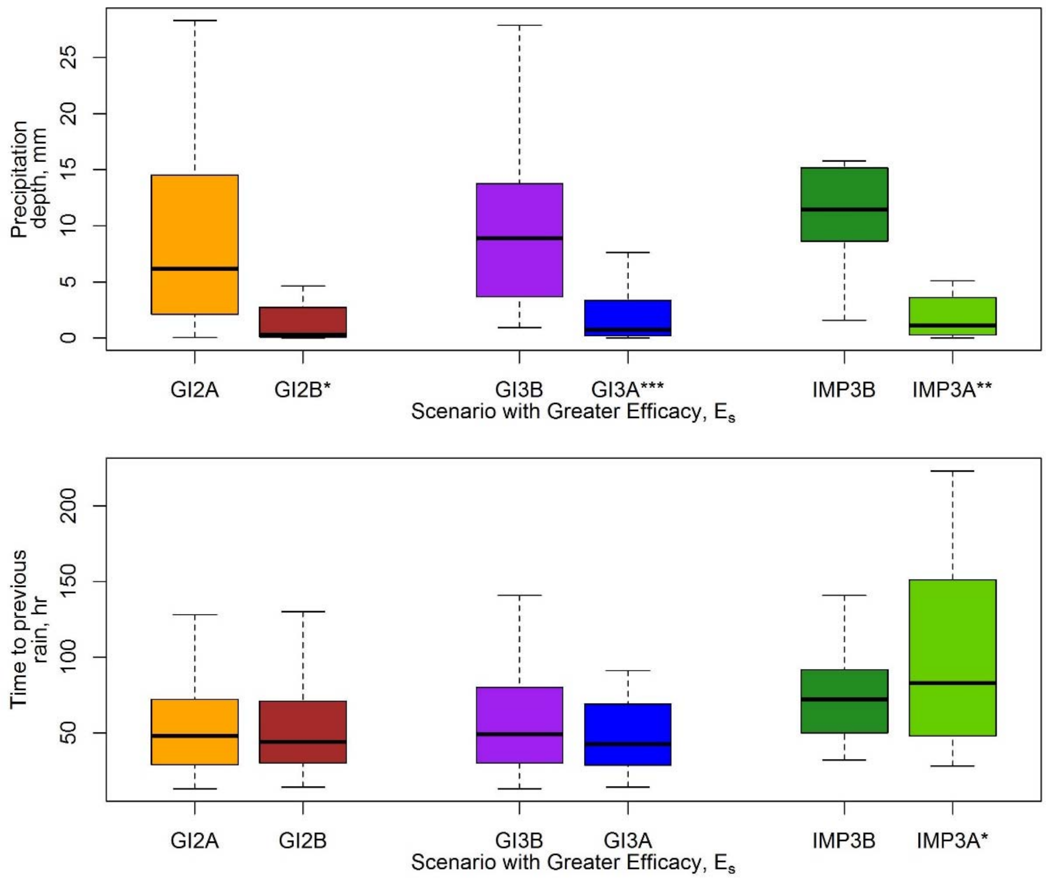


Figure 5.14. Paired spatial configuration scenarios efficacy comparisons and dependence on total event rainfall depth and time to previous rainfall event. *p<0.10; **p<0.05; ***p<0.0001

The statistical significance of the dependence of the binary state classification on total event precipitation depth and time to previous rainfall event was tested using a t-test of means. The null hypothesis that the state classification on the event conditions were independent was rejected if the p-value resulting from the t-test was less than 0.10. **Figure 5.14** shows box plots of the groups resulting from the classifications.

T-tests were significant for all of the paired spatial configuration scenarios' dependence on total event rainfall depth (p = 0.058, 0.00017, 0.0021, for GI2A/B, GI3A/B, and IMP3A/B, respectively). During larger events, spatial configuration scenarios where imperviousness located in high flow accumulation areas of the sewershed was removed/treated were more effective in reducing runoff volumes than spatial configuration scenarios located in low flow accumulation areas of the sewershed. The t-test for spatial efficacy's dependence on the inter-event period was only (marginally, $p = 0.095$) significant between the IMP3A and IMP3B scenarios. This result indicates that when events occur soon after a previous rainfall event, the spatial configuration where imperviousness is removed from high flow accumulation areas will perform better than the spatial configuration where imperviousness is removed from upslope areas. The tests on dependence on spatial configuration both provide evidence that downslope interventions (treatment or removal) are more effective than upslope interventions under wetter conditions, indicating that the downslope interventions are capturing not only their direct contributing areas but also some upslope area.

Empirical Data Quality Issues

As mentioned in Chapter 4, on a telephone call I had with the engineers responsible for instrumenting the site, sensitivity of the sensors to low flows were confirmed. Accurate low flow measurements in the sewer pipe were not prioritized compared to capturing quickflow response to rainfall events, especially flow peaks. Between the initial monitoring period, from 2011 – 2015, there was also a change in leadership in the management of this project. Several data quality issues were noted. First, raw data was provided to the researcher in different formats. The pre-GI empirical data appeared much more packaged: rainfall intervals and calculated in-pipe monitored flows had been discretized to consistent time intervals and date ranges for documented instrumentation problems were documented, for example. Second, the raw data between the two periods appeared to have been cleaned and processed to different standards. In particular, periods of low-flow signals were observed in the post-GI dataset. These could either have been an instrumentation error, or a signal from localized lawn watering or other input. The pre-GI flow data did not exhibit any signal similar to this. Third, as noted in a report by the engineering consultant, and confirmed by this research, the rainfall-runoff ratio in many cases *increased* after the installation of GI. This finding, coupled with the observation that a second instrumented "control" sewershed (not included in this study) also exhibited higher rainfall-runoff ratios (by 72%), during the 2015-2016 year compared to in 2010, despite 2010 having a greater total annual rainfall depth than the 2015-2016 period, and there being no construction changes in that watershed, suggests that the monitoring data may be limited in making before and after comparisons (LimnoTech, 2016).

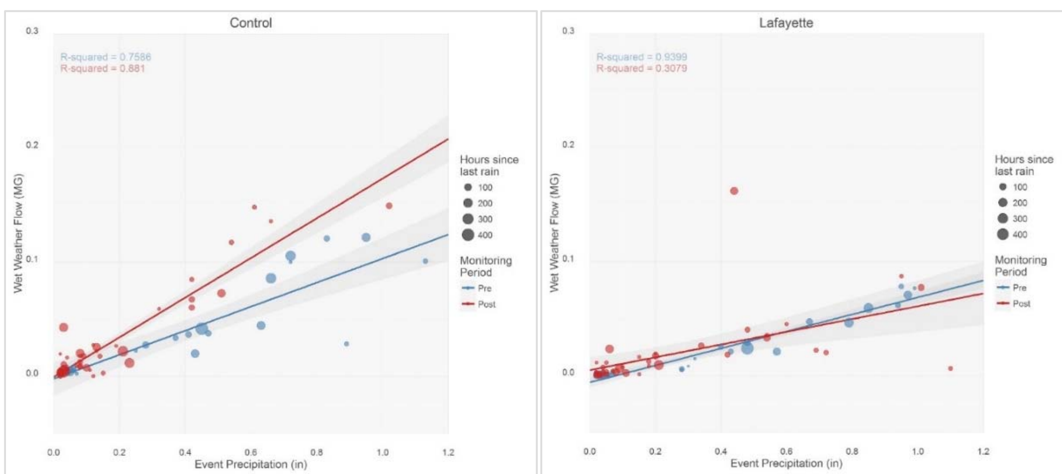


Figure 5.15 Empirical Rainfall-runoff ratios before and after GI construction. The left figure shows that on the control site, the post-GI period rainfall-runoff ratio was higher than the pre-GI period rainfall-runoff ratio. The figure on the right shows that for the Lafayette site, there does not seem to be a significant difference between the rainfall-runoff behavior pre- and post-GI installation. Source: LimnoTech, 2016.

Unfortunately, there was no way of knowing whether the pre- or post- GI monitoring data more accurately reflects the site. While the reduction in slope of the rainfall-runoff ratio is not statistically significant for the Lafayette site, it does appear that the post-GI condition suppressed what might have otherwise been an increase in the rainfall-runoff ratio that was observed in the control sewershed (Before-After-Control-Intervention, BACI, experimental setup).

Below is a summary of problems (incongruences) comparing simulated and empirical data.

1. Simulated forcing (2015) had a maximum rainfall event of 48 mm. Empirical (2015) forcing had a maximum rainfall event depth of 66 mm.
2. Post-GI empirical monitoring period systematically recorded greater flows than Pre-GI empirical monitoring period, despite smaller rainfall events, on average.
3. Empirical flows record response to actual rainfall intensities. Simulated flows are responses to averaged rainfall intensities (peaks will be dampened)
4. The full empirical flow records include events outside the growing season window, which are likely to result in more runoff, higher peaks, and larger rainfall-runoff ratios

As can be seen in **Table 5.4**, the event-based analyses allow for closer comparisons of the distributions of storm events and runoff response. Both the empirical rainfall-runoff (RR) ratio and the empirical event peaks are larger than the simulated RR and event peaks, by factors of 1.5 and 12.5, respectively. However, event rainfall totals for the empirical data are also greater by a factor of 1.6.

Table 5.4. Comparison of rainfall-runoff distribution summaries for simulated and empirical base case

	Min	Q1	Median	Mean	Q3	Max
Empirical Base Case (RR)	0.1	0.13	0.17	0.16	0.17	0.2
Simulated Base Case (RR)	0.01	0.05	0.06	0.07	0.07	0.13
Empirical Base Case (event peak, cms)	0.115	0.116	0.14	0.15	0.16	0.2
Simulated Base Case (event peak, cms)	0.0006	0.0016	0.0053	0.0056	0.0082	0.016
Empirical Base Case Rain 2010 (event total, mm)	0.5	2.03	11.12	19	17	76.9
Simulated Base Case Rain 2015 (event total, mm)	0.012	0.65	3.22	7.75	11.5	47.8

* Summarizes March - August window

Site Sensitivity and Flow Monitoring Sensitivity Analysis

While there were problems with the monitored data that prevent comparisons between the pre and post GI monitoring periods, the noise and measurement error in the monitoring data necessitates consideration of how the observed differences between scenarios' outputs compare in magnitude to the level of variation and precision possible with in-pipe flow monitoring. Although the computational intensity of running ParFlow simulations prevents parameter sensitivity testing, the changed parameters between the nine scenarios tested can be thought of as tests on the sensitivity of the entire site. The level of variation in the event-based runoff volumes compared to the variation observed in event-based volumes from the monitoring data provides one way of evaluating the sensitivity of the site to the scenarios' changes and the relevance of the magnitudes of difference in performance between the scenarios.

Previously, the total event rainfall depth was shown to be significant influence on the relative performance between different treatment spatial configurations. Total event rainfall therefore was included as an important control in assessing performance variation across scenarios. This was especially important since the empirical monitoring data also had a different rainfall profile than was used for the simulations, as described in the previous section. The measure of variation that was chosen therefore was the absolute width of the confidence percentile intervals estimated from the regression of the total event runoff volume on the total event precipitation event from the monitored rainfall and flow data from the pre-GI period. The confidence interval represents the area in which the ‘true’ mean runoff volume is likely to reside (with 95% confidence), and takes into account the number of observations available in the range, therefore is nonlinear in width, shorter when more observations are available, and larger when observations are scarcer. The post-GI monitoring period was not included in the quantification of variation in measured flows for reasons of data inconsistency and unreliability discussed in the previous section. The width of the confidence interval was calculated by taking the absolute value of the difference in the upper confidence interval limit and the lower confidence interval limit. Confidence interval upper and lower limits were determined by several confidence levels: 95%, 90%, and 85%.

If the mean differences between the scenarios’ total event runoff volumes is greater than the width of the confidence interval, this is an indication that the magnitude of the difference between the two scenarios might be large enough to attribute to outside the normal “noise” range of the base monitoring data. For example, the simulated runoff volumes per event for GI2A and Base are differenced. This difference is then regressed on the precipitation depths for each event. The resulting estimated slope for the regression represents the mean expected difference in volume between these two scenarios at a given rainfall event depth. If this expected difference is greater than the width of the confidence interval observed from the monitored data, this indicates that that difference is outside the bounds of confidence associated with the noise of monitored data, and the difference may be noticeable. **Figure 5.16a** shows the difference between the runoff volumes for base case and each of the scenarios, compared with the widths of the 95%, 90% and 75% confidence intervals. None of the scenarios exhibit a large enough difference with the base case to exceed the level of noise in the monitoring data at the 90% - 95% confidence levels. Only the difference in runoff volume from one scenario, GI2A exceeds the level of noise in the monitoring data at the 75% confidence level. Even the relatively dramatic increase in site imperviousness from 23,375 m^2 to 31,900 m^2 (36% increase) between Base and IMP2 did not result in a large enough difference to cross the barrier of noise in the monitoring data.

Differences in performance between different spatial configurations were even smaller, and not significant compared to the level of noise in the monitored data. None of the differences in event runoff volumes for GI2A/GI2B, GI3A/3B or IMP3A/IMP3B approached detectable levels.

Of all the combinations of scenarios simulated in this study, the maximum difference in mean event runoff volume was between IMP2 (maximum allowable impervious surface developed) and GI2A (all ROW surface area treated with GI). These configurations and parameterizations led to a performance difference that just barely crosses the 90% confidence interval of variation for the monitored data (**Figure 5.16b**).

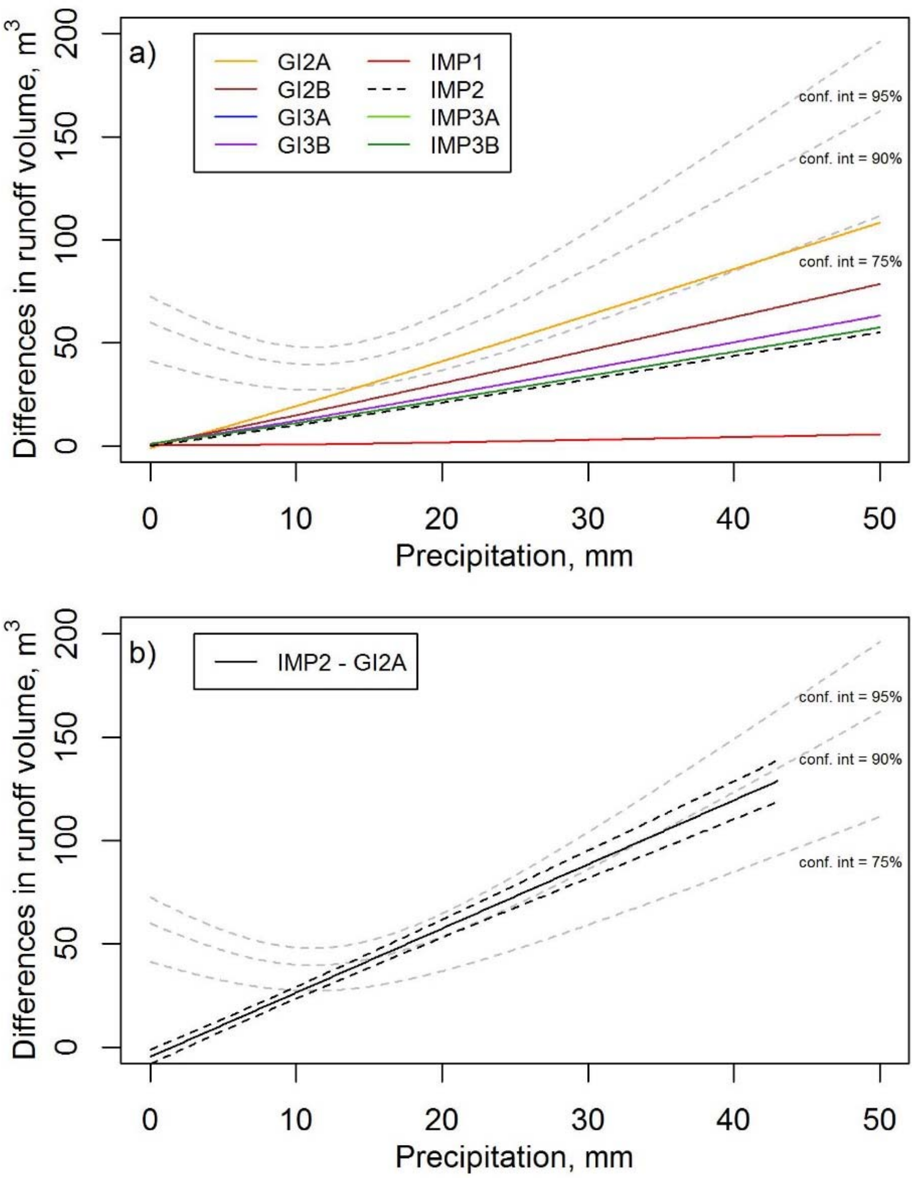


Figure 5.16 a) Comparisons between effect of each scenario and level of natural variation observed in monitoring data (gray dashed line). b) Comparisons of differences in runoff volume between maximum treatment difference scenarios, IMP2 and GI2A, and level of natural variation observed in monitoring data (gray dashed line).. The 95% confidence interval of difference in runoff volume, dependent on rainfall depth is shown with the black dashed line.

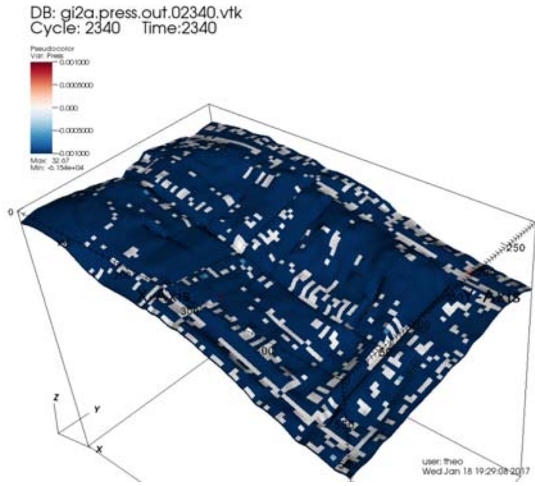
Surface-Subsurface Pressure Head Propagation

One benefit of applying the three-dimensional coupled surface-subsurface model ParFlow.CLM is that the any layer of the domain can be isolated to further study specific processes. In the previous section for example, an analysis of context-dependent differences in effectiveness revealed that interventions (treatment/removal) located in high flow accumulation areas in the sewershed resulted in greater effectiveness per square foot. Visual inspection of the three-dimensional positive pressure domain can reveal both where there is overland flow being generated, and how water infiltrates to the underlying layers. **Figure 5.17** shows a comparison of GI2A and GI2B, the paired spatial scenarios that exhibited the most difference in response.

Figure 5.17 is a three dimensional view of the site, from the southeast corner in the foreground to the northwest corner is the background. The blue-red coloration of pressure head is on a scale symmetric around 0, so that areas that appear blue have negative pressure, areas that appear red have positive pressure, and areas that are white are in a transition pressure, between positive and negative. The two columns show the same time slices through the rain event for GI2A and GI2B. Only the first three layers of the domain are shown (with a vertical exaggeration of 5x to make the site topography more apparent). When rain event first starts, the configurations of GI in each of the scenarios becomes apparent: in GI2A, which treats the ROW, impervious building footprints immediately begin to transition to positive pressure, while the ROW areas remain negative pressure. In contrast, in GI2B, the ROW, which is not treated with GI transitions first to positive pressure, while the building footprints retain their negative pressures for longer. Eventually, around time 2440 the two scenario domains appear similar.

However, when the event begins to recede, some differences are again notable. In time 2500, there is more positive surface pressure that appears to be connected to the treated

ROW areas in GI2A. Since retrofit pavement areas were assigned Manning's n values equal to those of pervious turf areas, positive pressures in the alleyways after the initial overland pressure wave associated with the event are not contributing much to the overland flow. Instead, they are intercepting delayed response flows from upslope areas. In a zoomed-in cross section of these alleys, which were not served by a burned-in pipe as the main ROW was shows the positive pressure continuing to build up in the alley ways, even after overland flow has passed **(Figure 5.18**).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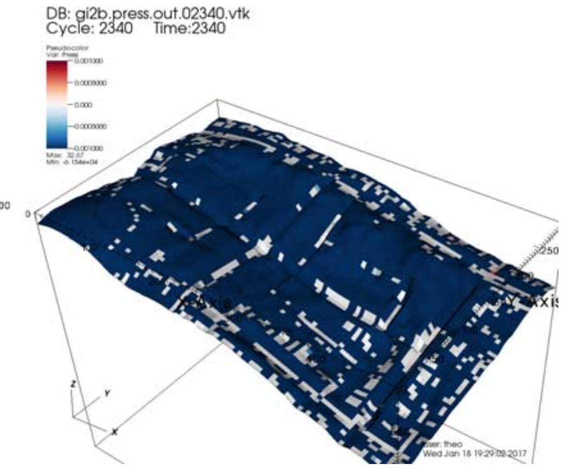
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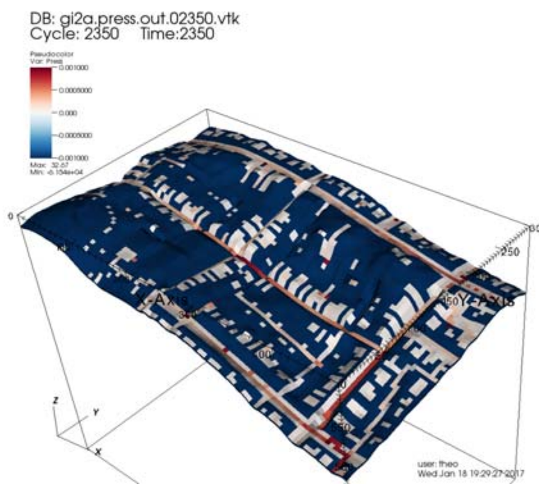
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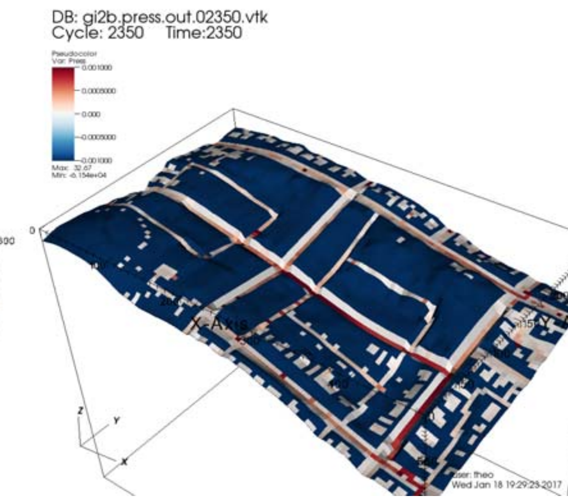
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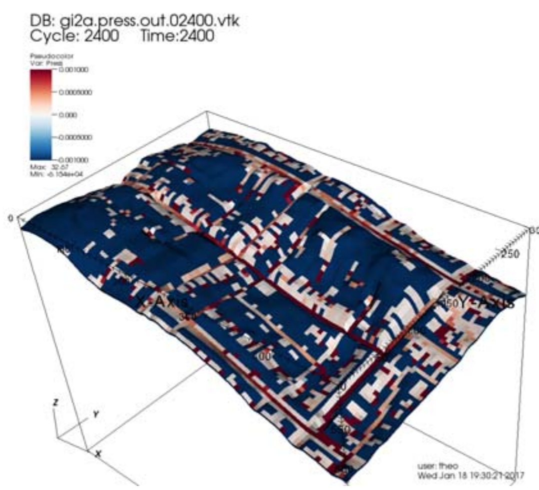
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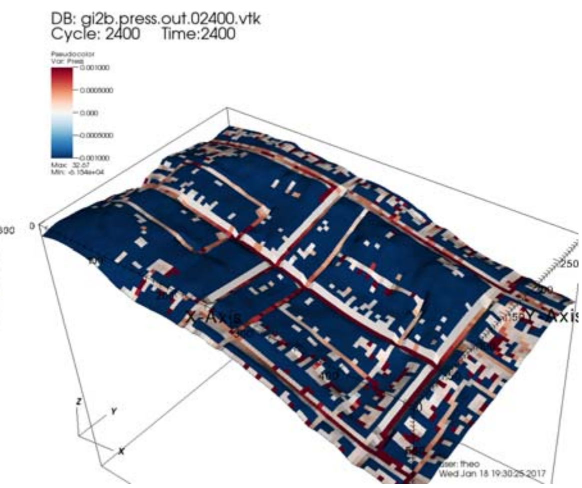
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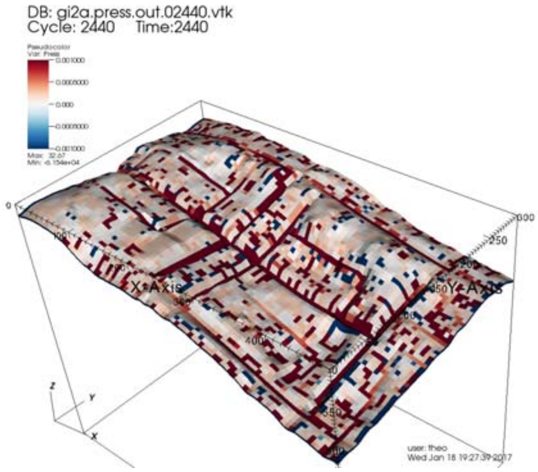
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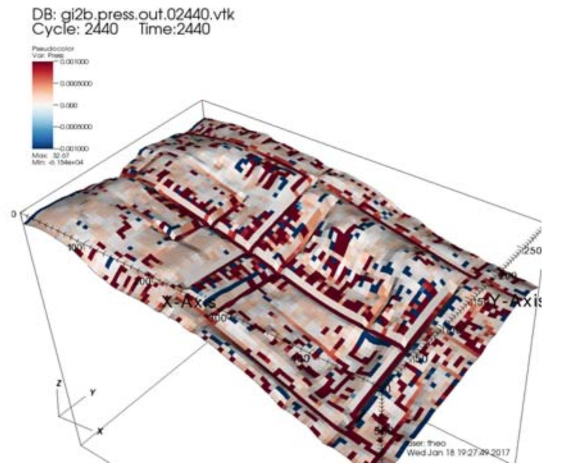
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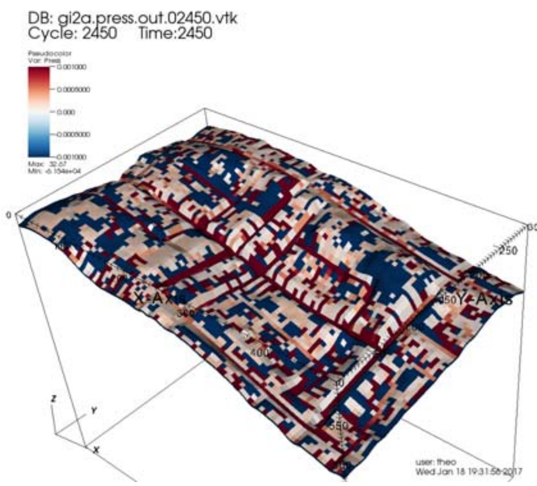
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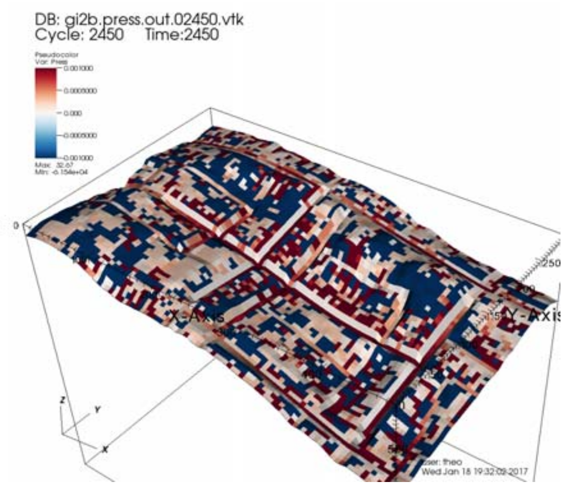
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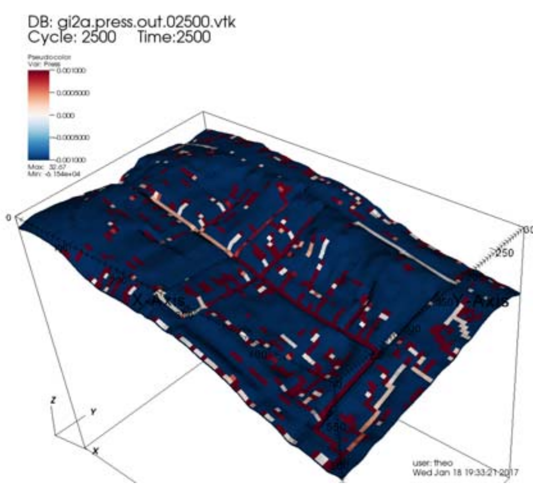
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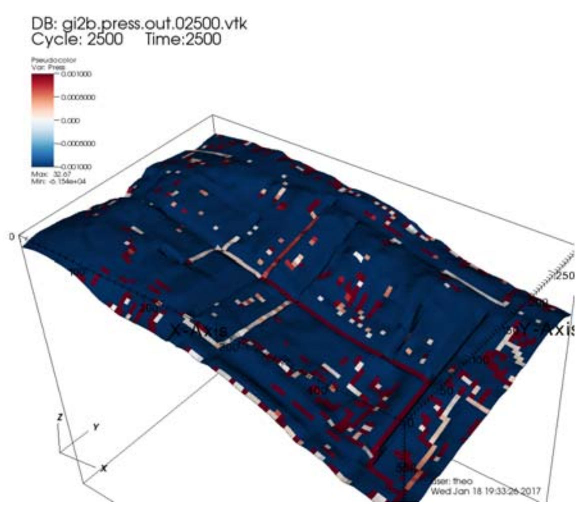
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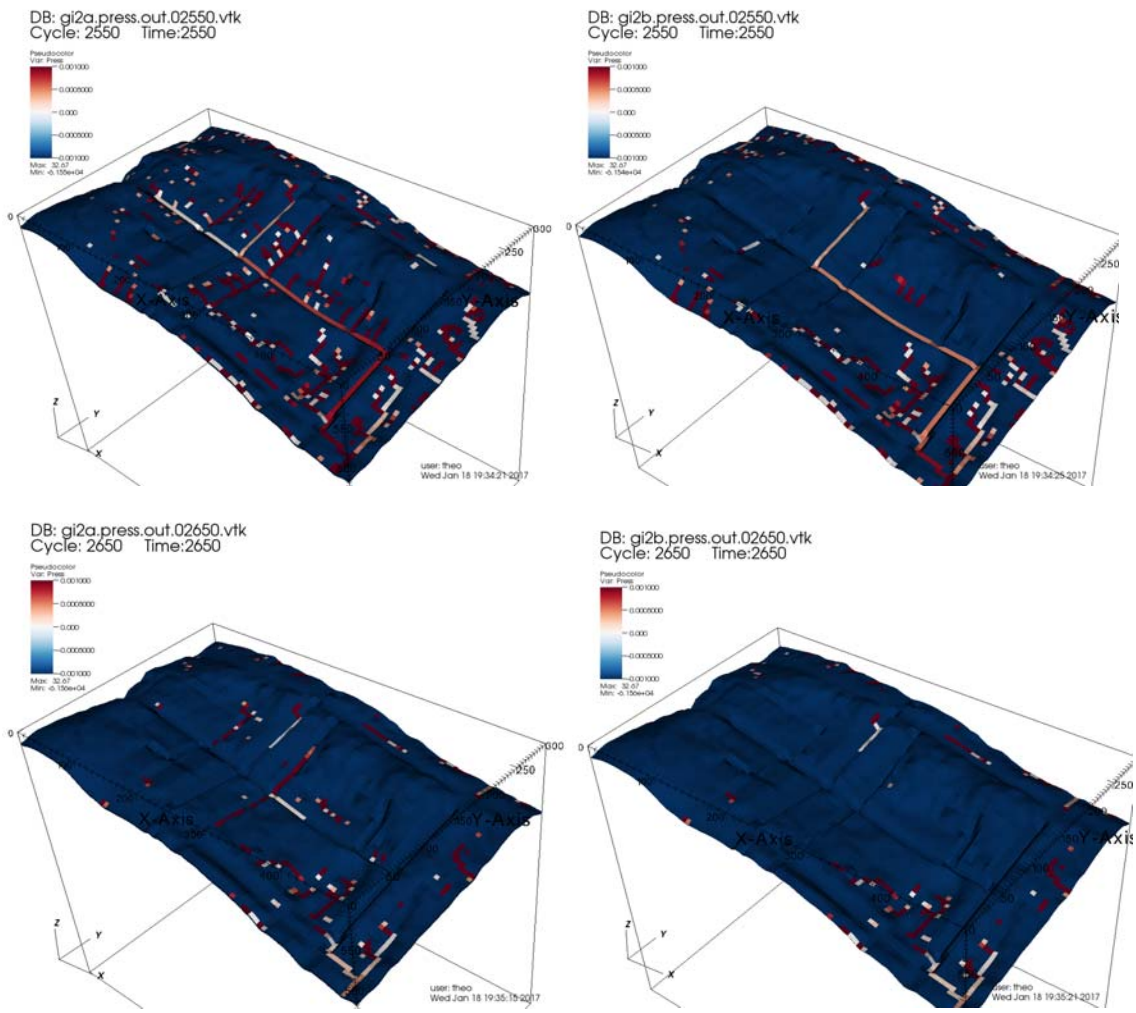

Figure 5.17. Comparisons between top three layers of domain response to rain event for GI2A (left) and GI2B (right). Color scheme from blue to red denotes pressure field centered at 0 pressure (white). Blue denotes negative pressure while red denotes positive pressure. By the end of the rainfall event , GI2A still exhibits high positive pressure in the alleys perpendicular to drainage system alignment. From examination of previous timesteps, it is clear that this high positive pressure includes contribution of upslope areas

of the properties adjacent to the alley.This positive pressure A longitudinal cross section of the alley is shown in **Figure 5.18**.

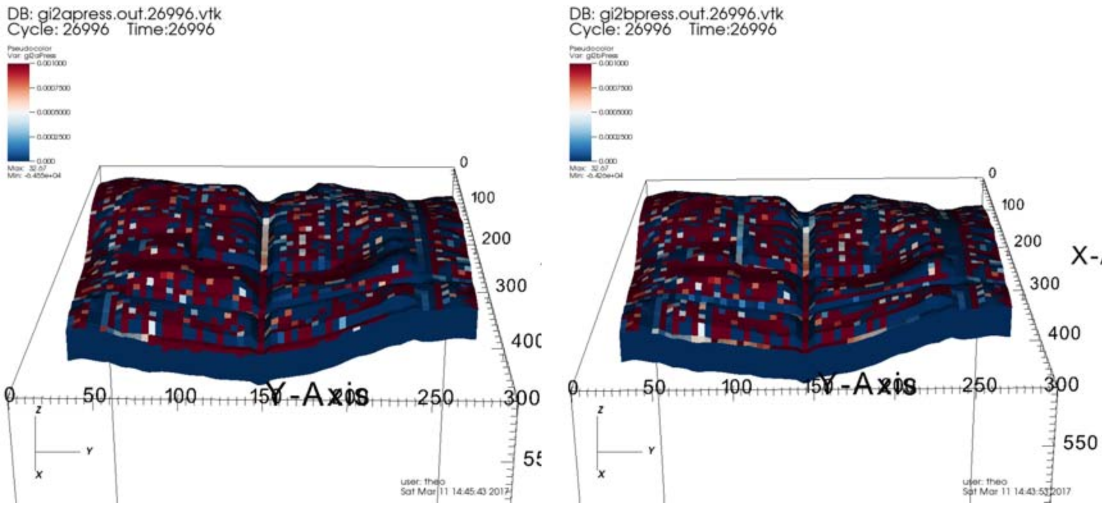

Figure 5.18 Cross section of alley where there is evidence of high pressure build up. Note that the main overland pressure wave has already passed through the central drainage alignment, and therefore appears in green. GI2A (left) alley shows continued interception of water in the retrofit alley, while GI2B does not.

DISCUSSION AND POLICY IMPLICATIONS

Table 5.5 summarizes the findings of this study. First, for the six-month simulation period of this study, there was not only no evidence that treatments located in high flow accumulation areas were less effective than treatments located in low flow accumulation areas, the evidence suggested otherwise. Both GI and impervious surface removal (and replacement with native soil) were able to mitigate more runoff volume from the site when it was located in high flow accumulation areas. This was shown to be the case because these areas were not only intercepting their designated treatment areas during the event, but also intercepting upland flows near the ends of the rainfall event period. The specifications of hydraulic conductivity and porosity used in this study, as well as the boundary conditions for the subsurface did not result in a limited capacitance situation. For example, because the groundwater table was located so far from the land surface, very little change occurred beyond the fourth layer of the domain, i.e., there was no evidence of groundwater mounding and very little accumulation of saturation or positive pressure head between rainfall events. Therefore, instead of limiting capacitance, wetter conditions caused green infrastructure in higher accumulation areas to intercept flows that otherwise would contribute to overland flow. Comparison of performance based on storm peak mitigation was also shown to be much less sensitive to spatial configuration than total event runoff volume. This may indicate that flow peaks are more dependent on overall magnitude of connectivity of land surface type, while volumes are additionally dependent on specific subsurface flow paths and topography of the site that are changed with spatial configuration.

Second, it was shown that while increased hydraulic conductivity from impervious to either green infrastructure or native soil resulted in observable differences in overland flow, there were no observable differences in the overland flow for green infrastructure vs native soil (e.g.: between GI3A and IMP3A). This finding may be related to the above finding in that the differences in hydraulic conductivity between native soil and GI may both not be constraining factors in watershed capacitance. Instead, the differences between paired spatial configuration scenarios (e.g.: between GI3A and GI3B) resulted in more observable differences. The site is more sensitive to changes in spatial configuration than changes in hydraulic conductivity, at least when the changes are only applied to only 7-9% of the site. If more of the site's hydraulic conductivity were changed however, there is some evidence that indicates that differences in runoff volume would be more observable, related to the third point, below.

Third, there was evidence that differences in runoff volume increased as the total treated area increased. The largest difference between paired spatial configuration scenarios was observed between GI2A and GI2B, which treated 14.2% and 15.6% of the site's impervious surface area, respectively, which was 5-7 percentage points greater than the treated areas in the paired scenarios GI3A/GI3B (7.3%/9.2%) and IMP3A/IMP3A (7.3%/9.2%).

Lastly, this study developed a way of contextualizing the significance of magnitudes of differences observed between different scenarios without having to perform multiple realizations of parameters in a sensitivity-analysis type study. Given the amount of variation and noise present in monitored pipe flow data for the study site, only the differences in response between IMP2 and GI2A resulted in a different large enough to exceed level of variation associated with 90% confidence interval from the observed flow data. The difference in impervious surface between these two scenarios was 30 percentage points. The difference between the Base and GI2A scenarios was large enough to exceed the level of variation associated with the 75% confidence interval. No other pairs of scenarios exceeded the level of variation in the monitored data.

There are several policy implications of this research. First, the spatial configuration of green infrastructure is an important consideration when deciding between treating ROW or dispersed treatments on private property within sewersheds of this development density. Treatment of ROW areas with GI is more effective than treatment of private roof areas with rain gardens because such treatment has the capacity to intercept more upslope areas. In particular, the reverse-crowned alleys capture runoff from upslope areas, and are also perpendicular to the drainage system, decreasing opportunities for water to find more flow paths toward the pipe system, and encouraging water to infiltrate in the alley area. While GI constructed in the ROW is also typically more costly than private retrofits both in terms of one-off design and construction costs and from continued maintenance costs, these higher cost may be justified in increased effectiveness. In addition, although not a part of this study, ROW projects are more easily tracked, monitored and serviced by centralized agencies, such as the DOEE or DDOT in DC and are therefore often able to be formally counted as part of an MS4 or CSO NPDES permit long term control plan. In contrast, private property retrofits still face challenges of durability, proper operations and maintenance and long-term tracking.

Second, within residential sewersheds of this development density, a 50% property treatment rate does decrease runoff volumes and peaks compared to not doing anything, but spatial configuration is unimportant. Therefore, when either designing a voluntary residential GI program, or an impervious surface removal program (e.g.: vacant home demolition), spatial configuration of treatment properties will not make a difference in overland flow mitigation. From a hydrological effectiveness point of view, there is no reason to devote resources to target participation from specific property owners at this scale.

Third, a combination of variation and measurement noise in pipe flow monitoring results in a barrier to the detection of potential differences attributed to site change. This applies to both increases in imperviousness of up to 15 percentage points, and treatment/removal of imperviousness of up to 30 percentage points. This study showed that only a decrease of 30 percentage points of imperviousness resulted in a detectable change in response compared to the amount of variation and measurement noise in pipe flow monitoring data. This 30 point decrease in imperviousness included both treating the ROW and a portion of building footprints, compared to the maximum allowable imperviousness for each property, highlighting the importance of residential participation in measurable mitigation of overland flows from urban sewersheds.

The problem of detectable change and noisy empirical data may also have a regulatory implication. As mentioned in both this chapter and the previous chapter, the selection of flow monitoring technology and procedures for data processing made before and after comparisons of the data very difficult, even with a BACI experimental design. The site used in this study is served by a separated sewer system, which means that the stormwater drainage system is designed to only convey wet-weather flows and expected to have zero baseflow during dry weather. The selection of the monitoring technology for the site, ultrasonic level sensors to measure stage height and the subsequent rating curve developed to translate stage height to flow, may not have consistently and reliably measured runoff response under these conditions. In addition, additional noise may have been introduced to the site through inputs not related to precipitation, such as lawn watering and car-washing in the neighborhood. Although empirical monitoring data analysis is typically held as the “gold standard” of experimental design, this study has shown ways that modeling can help fill in holes in understanding urban stormwater management, providing a way to “control” site conditions to conduct experiments about specific hydrological behaviors.

In short, at the sewershed scale, planners should focus on retrofitting public ROWs with GI, prioritizing locations of higher flow accumulation to capture delayed response that do not easily drain into the conventional storm drainage infrastructure. GI on private properties can help add to the effectiveness of roof downspout disconnections, but there is no need to target specific properties. Increasing overall participation amongst residents, rather than trying to “optimize” spatial location of dispersed GI should be the main goal of voluntary distributed GI programs. This is the subject of the following chapter.

Table 5.5 Summary of research findings

Treatment - Effect	Hypothesis	Finding
Spatial configuration of green infrastructure on overland flow	Green infrastructure located in high flow accumulation areas are less effective than treatments located in low flow accumulation areas during wetter conditions.	**Rejected.** Green infrastructure located in high flow accumulation areas is more effective than green infrastructure located in low flow accumulation areas.
Spatial configuration of impervious surface area removal on overland flow	Impervious surfaces removed from high flow accumulation properties will mitigate less overland flow volumes during wetter conditions.	**Rejected.** Impervious surfaces removed from high flow accumulation areas is less effective than impervious surfaces removed from low flow accumulation properties.
Hydraulic conductivity of treatment on overland flow	Increased hydraulic conductivity associated with green infrastructure retrofits will result in more mitigation of overland flows than merely replacing impervious surfaces areas with hydraulic conductivity of native soils, which will be more effective than merely disconnecting impervious areas from the drainage system.	**Partially supported.** Green infrastructure retrofits and impervious surface removal performed better than roof disconnection, but there was no difference in runoff response between scenarios that increased hydraulic conductivity of receiving pervious areas and scenarios that merely replaced impervious surface with native soil.
Magnitude of treatment on overland flow on differences between paired spatial configuration scenarios	Differences between paired spatial configuration scenarios will be more evident when the total magnitude of treated area exceeds 10%	**Supported.** The largest difference between spatial configuration scenarios was observed when total treated area exceeded 10%.
Treatment of impervious surface - detectable differences in pipe flows, compared to noise in monitoring data	Differences between scenarios' runoff volumes will be detectable when the difference between treated/removed impervious surface area exceeds 15%	**Partially supported.** Differences between scenarios' runoff volumes were predicted to be detectable with only 75% confidence for two scenarios that differed by 15.6% impervious area. Differences between scenarios' runoff volumes were predicted to be detectable with 90% confidence for only one pair of scenarios, which differed in imperviousness by 30%.

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CHAPTER 6: MORE ON DISTRIBUTED STORMWATER MANAGEMENT: SOCIAL NETWORKS AND INFRASTRUCTURE

INTRODUCTION AND BACKGROUND

Over forty years after the US EPA's passage of the Clean Water Act (CWA), 53% of river and stream miles and 69% of lakes, ponds and reservoirs in the US remain classified as "impaired" (US EPA 2015). "Green Infrastructure" (GI) is a multi-scale strategy that acknowledges the critical roles natural processes such as evapotranspiration and infiltration play in supporting healthy, sustainable societies (Benedict and McMahon, 2006). GI can be used to refer to the importance of regional scale conservation planning (e.g. riparian corridor protection and growth management) on hydrological regime and water quality. Within cities however, GI often refers to the implementation of best management practices (BMPs) for stormwater management that at least partially mimic the natural hydrologic cycle by promoting infiltration and evaporation of stormwater. Traditionally, BMPs included detention basins that were not necessarily designed to include green characteristics, but GI today more often refers to rain gardens, bioswales, porous pavement, and tree plantings that incorporate more of the natural hydrologic cylce. They are mean to bring cities into compliance with stormwater and sewage infrastructure CWA regulations while also improving overall environmental quality and livability and are often implemented at the site scale. This type of GI is implemented on a property-by-property basis, often by retrofitting sites to better manage stormwater runoff (US EPA, 2004; Mandarano and Paulsen, 2011; Young, 2011).

Understanding how to encourage and speed private property retrofits is particularly useful for post-industrial cities, which are likely to have slow redevelopment rates, stagnated population growth, and aging infrastructure in need of upgrade (Birch and Wachter, 2008;

Schilling and Logan, 2008)). Residential land use can make up over 50% of the land area in urbanized areas, making voluntary residential adoption of GI a potentially very cost effective means for cities to manage stormwater runoff, especially after ecosystem services co-benefits are factored in (Mandarano, 2011; Brown *et al.*, 2016). As I will expand on in the following section, previous research has explored the influence of financial incentives, environmental attitudes, environmental knowledge, and physical constraints on the potential for residential adoption of GI.

In this study, I examine the spatial-temporal patterns in which GI has actually been adopted by residents in Washington DC during the first six-years of a voluntary GI installation program called RiverSmart Homes. Unlike the results of surveys, in which residents are asked directly about willingness to participate based on their preferences, the analysis of empirical data adds two things. First, it illuminates how highly heterogeneous spatial distributions of physical and social factors have influenced actual adoption. Second, it allows us to explore the spatial implications of time-dependent processes of adoption, such as pathways of information dissemination. This research tests how participation is dependent on spatial distribution of socio-demographic and physical landscapes of the city and how the spread of participation also exhibits a space-time event dependence that can be associated with the locations of previous installations.

PREVIOUS RESEARCH

Conventional drainage infrastructure, including catch basins, pipes and cisterns, is typically located in the public right of way. Retrofits of existing impervious areas with GI to effectively manage runoff close to where it is generated is often referred to as 'source control'. Source control measures, such as rain gardens, require land surface area to intercept and retain or detain runoff volumes (Valderrama and Levine, 2012; Keeley *et al.*, 2013). Access to these areas can be gained through new development regulations or through encouraging property owners to retrofit their properties. Localities with limited local budgets and slow redevelopment rates see GI as a cost-effective alternative to conventional infrastructure, especially if GI can be constructed by retrofitting private properties rather than relying on public property and right-of-way projects (Valderrama and Levine, 2013).

Several studies have used surveys to determine the relationship between the residential uptake of GI and socio-demographic characteristics. Participants' stated responses reflect both public and private motivations to GI adoption. Stated public benefits include: general desire to improve the environment (Thurston *et al.*, 2008; Montalto *et al.*, 2012; Baptiste *et al.*, 2015), stormwater control (Sun and Hall, 2013), better water quality and hydrological improvement (Londoño Cadavid and Ando, 2013). Stated private benefits include: owners' desire to reduce personal property flooding (Londoño Cadavid and Ando 2013), financial savings when subsidized installations are offered (Brown *et al.*, 2016), and access to an unregulated source of irrigation water (Brown *et al.*, 2016). Although participant survey responses yield insight into individuals' preferences for environmental services, research has shown that actions can differ substantially from stated intentions (Diamond and Hausman, 1994; Portney, 1994).

One potential source of difference between stated responses and actual program participation is that responses to surveys reflect the respondent's preferences assuming he or she is aware of the program in question. In reality, awareness about voluntary programs may be a stronger determinant of participation. Many have suggested economic incentives as one way to increase awareness of strormwater management and encourage private adoption of GI. These incentives work through pricing the externality of runoff production and crediting property owners that treat or manage their own stormwater runoff

(Sample *et al.*, 2003; Parikh *et al.*, 2005). The logic of economic incentive strategies is based on an assumption of economic rationality where property owners will invest in GI construction if they can achieve long-term cost savings on stormwater fees. However most studies demonstrating the effectiveness of such approaches are theoretical rather than empirically-based. After taking into account the time that knowledge about fees, credits and GI retrofits takes to travel through social networks and individual decision-making processes, adoption rates have been shown to be much lower than when perfect economic rationality is assumed (Montalto *et al.*, 2013).

Infrastructure managers have also reported that limited public knowledge about stormwater issues and lack of familiarity are barriers to widespread adoption of GI (de Graaf and der Brugge, 2010; Keeley *et al.*, 2013). Resident unfamiliarity with GI programs may also deter them from participation. Interviews carried out with participants in an economic-incentive based GI program confirmed that the decision to participate represented having taken a risk. In overcoming this risk, one third of interviewees expressed that “word-of-mouth” and “project presence” played a significant role in the decision to participate (Brown *et al.*, 2016).

Few empirical studies address the spatial patterns of residential GI adoption. An empirical study of a subsidized, voluntary rain barrel program showed that adoption counts were related to the social characteristics of neighborhoods, including “green” political party voter proportions and home ownership rates (Ando and Freitas, 2011). In addition, this study showed higher adoption rates in locations nearer to rain barrel distribution sites and near long-term GI demonstration and information dissemination sites. Another study of a two-year experimental residential rain garden adoption program showed more spatial clustering near previous adopters than would have been expected due to chance accounting for the heterogeneity in the spatial configurations of parcels (Green *et al.*, 2012). These studies reveal a move from static personal attributes as drivers of GI adoption towards understanding the influences of time-dependent information dissemination and social capital on GI adoption.

Yard landscaping practices have also been framed as expressions of personal preferences as well as functions of historical and modern social norms. Research shows that residents' yard landscaping practices are extensions of self-image that respond to cultural norms and that vegetation choices exhibit mimicry among neighbors (Zmyslony and Gagnon, 1998; Larsen and Harlan, 2006; Nassauer *et al.*, 2009). Therefore, we might expect the participation of resident in a GI program to have some influence on his/her neighbors' propensity to participate in the program. Participation in a voluntary GI program may similarly be socially influenced since it reflects both landscaping preferences and requires residents to gain awareness of the program. Gaining awareness of the program itself is a process of information dissemination. Others have suggested "epidemic" models of technology diffusion to express the spread of new information (Geroski, 2000; Jaffe *et al.*, 2002). In these models, imitative behavior is primarily influenced by the spread of information through proximity-dependent social networks. Empirical research has demonstrated the utility of information dissemination models for explaining highly visible behaviors, such as residential solar panel installation (Rode and Weber, 2016), automobile purchasing (Grinblatt *et al.*, 2004), and recycling (Hopper and Nielsen, 1991). When neighbors are exposed to "nudging" information, even a non-visible environmental behavior, such as energy and water consumption has been shown to be influenced by neighbors' behaviors (Allcott, 2011; Jain *et al.*, 2013). Normative social influence, which relies not only on sharing of information, but also on communication of behavioral standards ("the *right thing* to do"), has been shown to be influential, even if residents do not report it being a major rationale for behavioral change (Nolan *et al.*, 2008; Schultz *et al.*, 2016).

From the above, we can hypothesize two major causes of observed spatial patterning of voluntary GI. First, adoption rates may be determined by the spatial heterogeneity of social and physical conditions with the city. Second, the locations of participants may be determined by time-dependent information diffusion, which may influence spatial clustering of adoption. In the latter, emphasis is shifted from the physical and social conditions that drive residents to independently adopt GI towards understanding how residents learn about the program and subsequently decide to participate. If participation locations are dependent on the spatial locations of previous GI installations, even after controlling for the tendency of properties and residents with similar characteristics to cluster together, this is evidence of previously uncaptured spatial processes of program growth. Understanding the spatial-temporal growth of voluntary GI programs can help urban watershed managers who leverage ambassadorial behaviors or key demonstration sites in residential areas to efficiently disseminate information that promotes residential participation in environmental programs (Hopper and Nielsen, 1991; Castaneda *et al.*, 2015). This is important because if previous installations and participants influence the participation of their neighbors, municipalities might anticipate savings on future outreach budgets and plan for when a program may begin to grow on its own. Quantifying this type of influence also begins to suggest the range of timeframe necessary for adapting urban landscapes to future conditions through private landscape management.

CASE STUDY: WASHINGTON DC RIVERSMART HOMES PROGRAM

Program Description

The case used in this research is the RiverSmart Homes Program, administered by Washington DC's Department of Energy and the Environment (DOEE). RiverSmart Homes is a voluntary stormwater retrofit program that provides subsidized installations of GI to residents. The purpose of the program is to help residents reduce stormwater runoff from their properties. It offers subsidies to adopt rain barrels, rain gardens, bayscaping (native plant landscaping), permeable pavement or shade trees on their properties. Homeowners make a copayment for each of the installations: $45 per rain barrel, $50 per shade tree, $75 per rain garden (limit one), $100 per bayscaping installation (limit one), and up to $1200 for the removal of impervious surface area and installation of permeable pavers. Participants are informed that they are required to maintain the installed features while they own the property.

The process of becoming a RiverSmart Homes participant involves the resident finding out about the program, contacting RiverSmart Homes staff to schedule an initial appointment (usually through an online scheduler) to assess which installations would be feasible on the property, deciding which type of GI is desired (if any), scheduling a contractor to install the GI and lastly installing the GI. The DOEE completes about 1,100 audits each year. Based on pilot programs administered by DOEE starting in 2007, DOEE specifically sought to eliminate barriers to participation including inability for non-car owners to transport materials to their homes, lack of understanding about installation and maintenance of GI (DC Water, 2015). Project funding has been provided through EPA 319 grants, American Recovery and Reinvestment Act funds, the Anacostia River Clean Up and Protection Fund, and Municipal Separated Sewer System (MS4) funds (DC Water

2015). The geospatial location for each RiverSmart homes installation was recorded between 2009-2015. Dates of adoption for each participant are also available. **Figure 6.1** shows the overall participation trend over time. Through 2014, there were 3,737 RiverSmart Homes installations on 2,836 unique properties, which represents 2.5 percent of all residential parcels in DC. The most popular installation was rain barrels (63%), followed by bayscaping (17%), rain gardens (14%), and lastly trees and permeable pavers (3% each). **Figure 6.2** shows a map of the density of all GI installations through the RiverSmart Homes Program, overlaid on total populations of each of the district's census tracts. It is clear that there is spatial clustering of adoptions within the city.

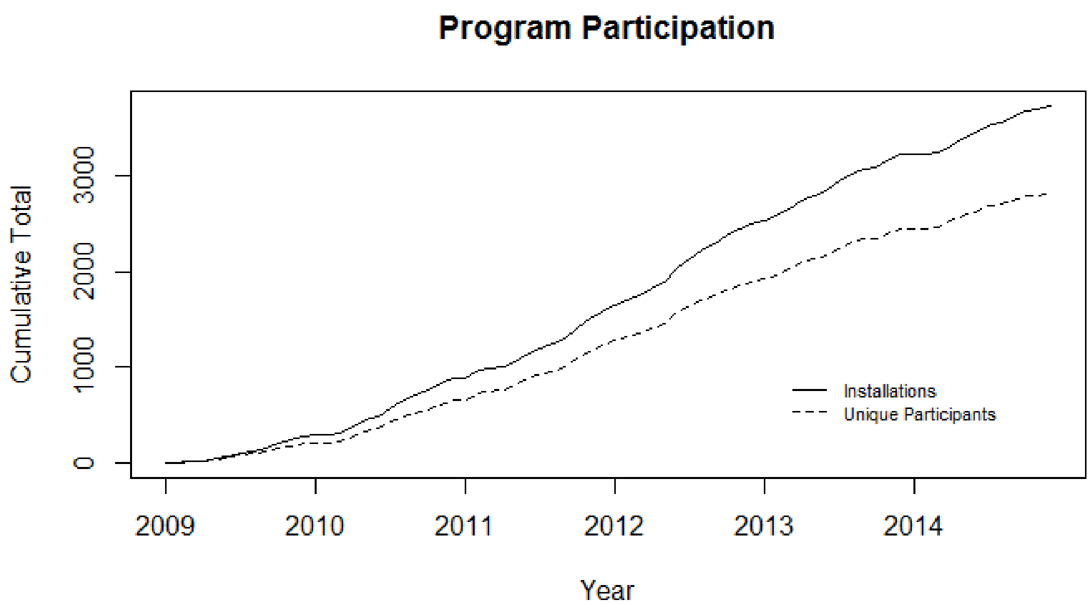

Figure 6.1 RiverSmart Homes program participation over time

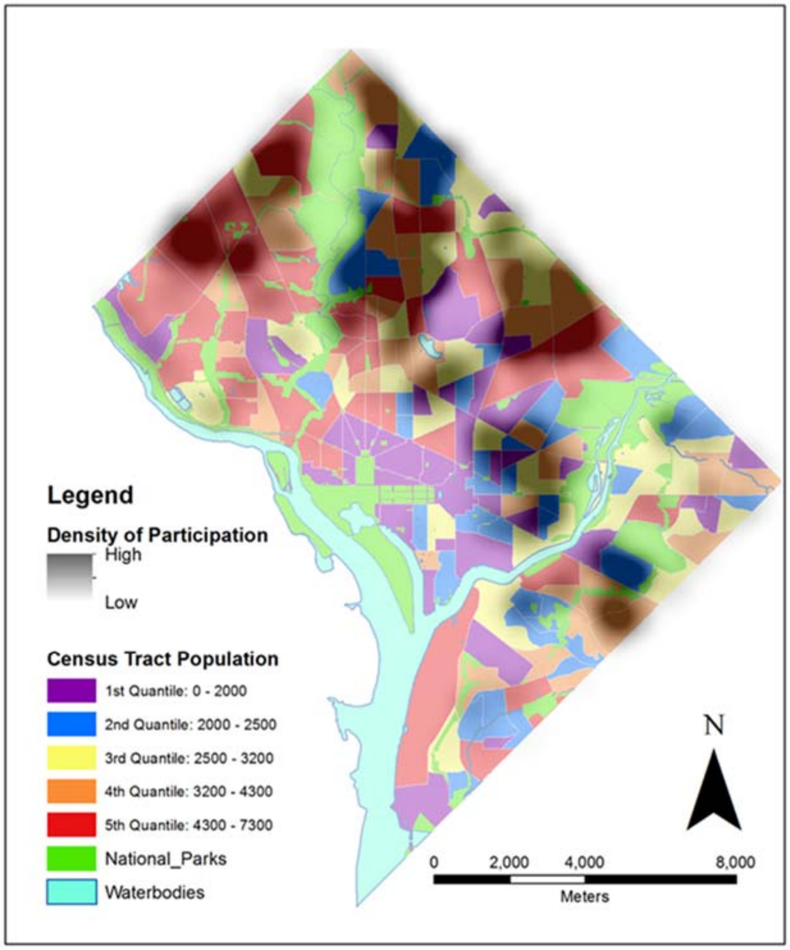

Figure 6.2. Density of all GI installations through the RiverSmart Homes Program from 2009 – 2014, overlaid on total population per census tract.

In 2014, DOEE administered an online survey (>800 responses) of participants' experiences with their GI installations. The survey included a question asking participants how they initially learned about the RiverSmart Homes program. **Figure 6.3** shows that the majority of respondents learned of the program through friends, family or a past participant. What remains unknown is the extent to which these informational networks resulted in spatial patterns. This is what I will investigate in this chapter.

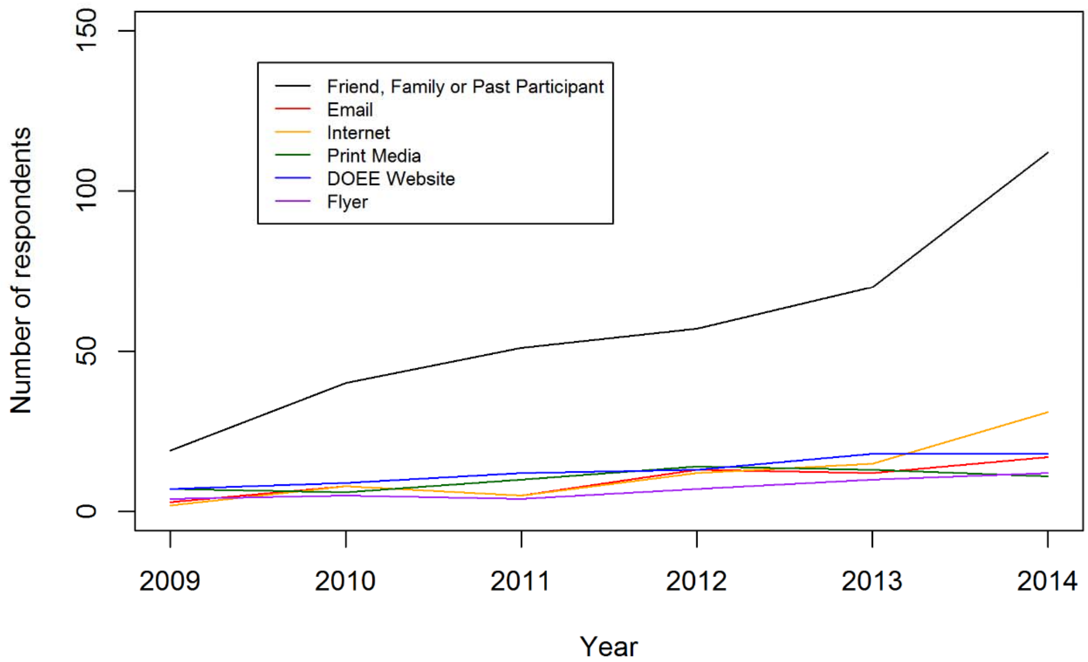

Figure 6.3. Survey responses from RiverSmart Homes participants to how they initially learned of the program.

METHODS

Overall Adoption Rate Regression

The regression of overall adoption rates between 2009 – 2014 on neighborhood characteristics captures the effects of spatially-dependent factors that influenced early residential GI adoption. Previous literature indicates that both physical form and social characteristics of neighborhoods are likely to reflect information dissemination and landscaping preferences. Therefore, two sets of explanatory variables, for physical and demographic neighborhood characteristics are included. The regression is specified as in **Equation 6.1**.

$$\log(GIcount_i) = \alpha + \delta\log(tothh_i) + \boldsymbol{D}_i\boldsymbol{\beta} + \boldsymbol{P}_i\boldsymbol{\gamma} + u_i \qquad [6.1]$$

where $\log(GIcount_i)$ is the log of the total number of GI installations for census tract i; $\log(tothh_i)$ is the log of the total number of households in census tract *i*; $\boldsymbol{D}_i$is a vector of census tract i's demographic variables and $\boldsymbol{P}_i$ is a vector of census tract i's physical variables. The demographic and physical variables included are shown in **Table 6.1.** Nested models of the full global model presented in (1) were estimated to compare the explanatory power of the model with only physical variables $\boldsymbol{P}_i$ (the global physical model) versus the model with only demographic variables $\boldsymbol{D}_i$ (the global demographic model). The maximum likelihood ratio test was calculated on the ordinary least squares regressions to quantify the explanatory strength of the global physical and global demographic models. Variance Inflation Factors (VIFs) were also calculated to ensure that variables included in each model did not exhibit extreme multicollinearity, which could result in unreliable coefficient and standard error estimates.

Spatial autocorrelation, a violation of the ordinary least squares assumption that observations are independent and identically distributed, is a symptom of social influence, diffusion processes, and missing spatially correlated variables (Anselin and Griffith, 1988). The problem of spatial autocorrelation has been shown to result in inaccurate (artificially low) measures of standard error associated with the estimated coefficients (Hoechle, 2007). While the coefficient estimates themselves will not change, standardized coefficients, which are needed to draw conclusions about the explanatory strength of each of the variables included in the model will be influenced by mis-estimated standard errors. Calculation of Moran's I on the residuals for each model is a common method of determining the extent to which the amount of variation in the data unexplained by the model may be biased due to uncaptured spatial autocorrelation.

To address this problem, the specification shown above was also used to estimate a geographic weighted regression (GWR) on the standardized variables included in the full global model. GWR generalizes the assumptions that observations are independent and identically distributed, and is used to demonstrate extent of spatial variability of estimated coefficients between census tracts through distance-weighting the results of repeated regressions (Fotheringham, 2009). Through a cross-validation, leave-one-out technique, a kernel weighted bandwidth is chosen to determine how spatially correlated coefficient estimates will be determined. Smaller bandwidths allow GWR coefficient estimates to be highly dependent on nearby neighbors' estimates and reflect high levels of spatial dependence (Bivand, 2017). The selection procedure for the adaptive bandwidth and the GWR coefficient estimation were performed using the 'R' package 'spgwr'. The chosen kernel weighting scheme was based on a Gaussian distribution. One GWR model is fit for each of the 172 census tracts included in the study. An alpha = 0.05 significance level determined the significance of each census tracts' GWR-estimated standardized coefficients. The set of GWR model estimates are centered on the OLS regression (the full global model) estimates.

Linear regression was chosen to maintain interpretability of the estimated coefficients. The log transformation of the total count of GI installations aided in ensuring a more normal distribution of residuals from the estimated models. The presence of GI adoptions was treated as latent propensity to adopt GI. To avoid biasing the model coefficients from removing zero-valued census tracts from the analysis however, these census tracts were assumed to have low propensity of adoption, and a small value (0.1) was added before taking the log. Theoretically, this treats number of adoptions per each census tract as a proxy for the latent propensity of residents within the census tract to participate in the program. Summary statistics for each type of GI and the attributes of the census tracts are shown in **Table 6.1**.

Table 6.1. Summary statistics for overall GI adoption and census tract attributes

	Minimum	Median	Mean	Max	Std Dev
Green Infrastructure Adoptions (2009-2014)					
Total Installations	0	14	28	215	40
Rain Barrels	0	7	14	107	19
Rain Gardens	0	1	3	30	5
Bayscaping	0	2	4	37	6
Permeable Pavement	0	0	1	5	1
Trees	0	3	7	57	10
Demographic Variables					
Total Households	545	1519	1681	5375	786
Median Home Value	$ 133,970	$ 478,615	$ 1,747,378	$ 70,663,950	$ 7,710,653
Total Population	1025	3315	3573	8036	1384
Total White	0	894	1427	6687	1559
Total Black	44	1639	1782	5219	1264
Total Asian	0	75	127	897	159
Pop < High school ed	0	15	14	70	9
Pop with Bachelor's Deg	0	26	32	100	29
Percent in Poverty	2%	14%	18%	53%	11%
Median Income	$ 14,813	$ 68,606	$ 74,053	$ 231,042	$ 41,489
Unemployment Rate	0%	10%	12%	40%	9%
Owner	17	558	633	2099	399
Renter	70	781	886	3360	559
Percent Non-English	0.00%	0.08%	0.15%	1.34%	0.24%
Physical Variables					
Mean res parcel area	190	1203	1605	12666	1439
Mean percent impervious	16%	43%	46%	100%	16%
Mean percent tree canopy	0%	19%	23%	60%	13%
In MS4 (dummy)	0	0	0.30	1	0.46

The explanatory variables included in the regressions were assembled from various sources and aggregated to the census tract level, which is a unit of analysis intended to act as a proxy for neighborhoods. Physical variables included: mean area of residential parcels, mean percent impervious of residential parcels, and mean tree canopy cover of impervious parcels. The mean area of residential parcels was calculated by selecting the properties with use code descriptions including the word “residential” (including: single family, multi-family, mixed use, etc) according to the Government of the District of Columbia Office of Tax and Revenue classifications (http://app.cfo.dc.gov/services/tax/property/pdf/usecodes.pdf) and the property lot shapefile from the District of Columbia Open Data portal (http://opendata.dc.gov/datasets/1f6708b1f3774306bef2fa81e612a725_40). The mean area of residential parcels per census tract was log transformed to correct for a right skewed distribution. The percent impervious and percent tree canopy were calculated using Zonal Statistics (ArcGIS Desktop 10.4) tools to summarize raster land use classification types per each residential property boundary. High resolution (1 meter x 1 meter) raster data classifying urban land cover in DC into six classes (base soil, buildings, roads/railways, other paved surfaces, tree canopy, and water) was obtained from the University of Vermont (University of Vermont, 2011). Land cover for this dataset was derived using orthorectified leaf-on multispectral imagery. Each parcel’s existing land cover percentages were aggregated to the census tract level by averaging percent tree canopy cover for all residential parcels in the census tract. Demographic variables included: median household income, percent renters in the census tract, percent non-English speaking population, population density, percent white, and median home value, among others. All demographic variables came from 2010 US Census. The distribution of each variable to be included was examined to limit the influence of skewed distributions and outliers. Median household income was log-transformed to correct the right-skewed distribution and percent white was represented as a dummy variable (=1 if > 80% white) because of a clear bimodal distribution in the data. The percent of the census tract in which English was not the primary household language was represented as a dummy variable (=1 if > 0.3%) to capture the effect of long right tailed distribution. **Table 6.1** shows summary statistics for each of the variables considered for the regression.

Shuffle Test

In order to test for evidence of spatial-temporal dependence of GI adoption patterns, I used a Monte Carlo randomized permutation resampling technique called the ‘shuffle test’ (Anagnostopoulos *et al.*, 2008). This test works through resampling the same population of participants many times, randomizing only the time of participation, and comparing distance-based metrics between the time-randomized (simulated) distribution and observed (empirical) distance-based metrics. Unlike the above regression analyses, the shuffle test, “controls” for the effects of individual level heterogeneity through the assumption that personal and property attributes typically remain unchanged over time. The simulated distribution therefore isolates the effect of order of participation by creating a counterfactual distribution of participation orderings likely to occur given no time dependence of participation location. The observed metric (for which we are interested in testing extent of time-dependence) is then compared to this simulated “shuffled” probability distribution. Significant departure of the observed metric from the simulated probability distribution indicates that empirical participation locations were dependent on the locations of previous participations.

Rejection of the null hypothesis indicates that the location of participation cannot be ruled out as independent from the timing of previous participants. The strength in resampling techniques improves the findings of the survey administered by the District by experimentally testing how spatial program growth may not merely be a function of personal or property characteristics, but also on exposure to previous participants. It also is able to isolate the effect of proximity to a previous participant from individual and neighborhood characteristics that are difficult to obtain data on, and which result in omitted variable bias and spatial autocorrelation. If all such individual-level variables could be measured and included in a regression, then the detection of spatial-temporal dependence in the shuffle test would be similar to identification of the estimated effects of spatial and temporal lags in regression.

I chose two metrics to represent exposure to GI: mean distance to closest previous program participant (DTC), and the number of previous participants within a 200-m radius (R200). Proximity-based, time-dependent exposure pathways may include a resident observing a RiverSmart Homes sign while passing a previous participant's property, previous RiverSmart Homes participants talking about their installations to their neighbors, or a potential participant inquiring about a neighbors' landscape upgrades. For each year t from 2010 to 2015, the set $GI_{t,total}$ includes all participants that have participated in the program at any time, from t = 2010 to the current time, t_{cur}. The set $GI_{t,prev}$ includes participants at time t that participated between t = 2010, … , t_{cur-1}. The set $GI_{t,cur}$ includes participants in t_{cur} only. The simulated probability distribution is created by randomly assigning (with probability = 0.5) each installation location in the set $GI_{t,total}$ to either $GI_{t,cur,i}$, or $GI_{t,prev,i}$, where i indicates the i^{th} simulation iteration set. Then, the two metrics, DTC_i and $R200_i$ are calculated using the actual geographic coordinates of participants with the random assignment for the i^{th} iteration. The simulation is repeated for $i \epsilon (1, \ldots, N)$ to form the time-randomized simulated distribution, where N is the total number of iterations (500). The observed metrics DTC and R200 for t_{cur} are compared to the simulated distributions for these metrics.

Figure 6.4 illustrates possible comparisons between the observed metrics and the metrics from a randomized iteration. For DTC, socially influenced clustering near previous participants would result in an observed mean distance that is on average less than mean distances from the time-randomized simulations. If there is no evidence of socially influenced clustering, then on average DTC should be about equal to the distances from the time-randomized simulations. Another type of time-dependent patterning is if observed DTC are actually longer than the time-randomized simulations. This could occur if time-dependent outreach activities happening in specific neighborhoods outweigh neighbor-to-neighbor dynamics. **Figure 6.4** illustrates similar comparisons for the R200 metric.

The choice of the time discretization (yearly) was chosen to help isolate the effect of information dissemination through the GI installations and previous participants themselves. The DOEE did provide promotional materials to community groups, non-profit organizations and at neighborhood-based fairs. These promotional activities would likely have a short-lived spatial effect on the spatial locations of participants. For example, in the days to weeks following a neighborhood promotional event, the DOEE confirmed seeing spikes in participants from that neighborhood. In this case, if the first participant reacting to such an activity had GI installed on her property and was followed by another participant in the neighborhood reacting to the same activity on his property several weeks later, then at the weekly scale, participant two might appear to have been "influenced" by his neighbor's (participant 1) installation. In fact both participants were responding to a location-based promotional activity. Discretizing time with longer intervals minimizes the effect of short-lived, spatial influences that increase participation. **Table 6.2** highlights the spatial and temporal scales associated with participants' answers to the question "How did you find out about the RiverSmart Homes program?" that reported in the online survey (2014). Social interactions that are both spatially determined and likely to happen on longer (months to years) time scales that are dependent on spatial locations include interactions with neighbors or through prolonged information dissemination through a neighborhood or other spatially-based group.

Table 6.2 . Informational pathways to RiverSmart Homes and spatial-temporal scales

Reported Means of Information about RSHomes	Space Dependence Scale and Example Process	Time Dependence Scale and Example Process
Friend, Family, Neighbor	**Close:** Neighbors talking **Far:** Friends across town talking	**Short:** Talking about the program in the days right after installation **Long:** Talking about the program months later when a neighbor notices the rain barrel in the front yard
Email	**Close:** Neighborhood listserv email blast **Far:** City-wide affinity group listserv email blast	**Short:** Response to email blast in days following **Long:** Repeated email blasts sent for many months
Internet	**Not Space Dependent**. People from across the city all can access the Internet	**Not Time Dependent.** People from across the city can access content at any time
Print Media	**Not Space Dependent.** For example, newspapers distributed all over city	**Short**: Response to an advertisement in the days after print
DOEE website	**Not Space Dependent.** For example, people from across the city all can access the Internet	**Not Time Dependent.** People from across the city can access content at any time
Flyer	**Close:** Flyer posted at a local grocery store seen by many neighbors **Far:** Flyer posted all over the city	**Short:** Response to flyer in the days to weeks that it is posted or distributed

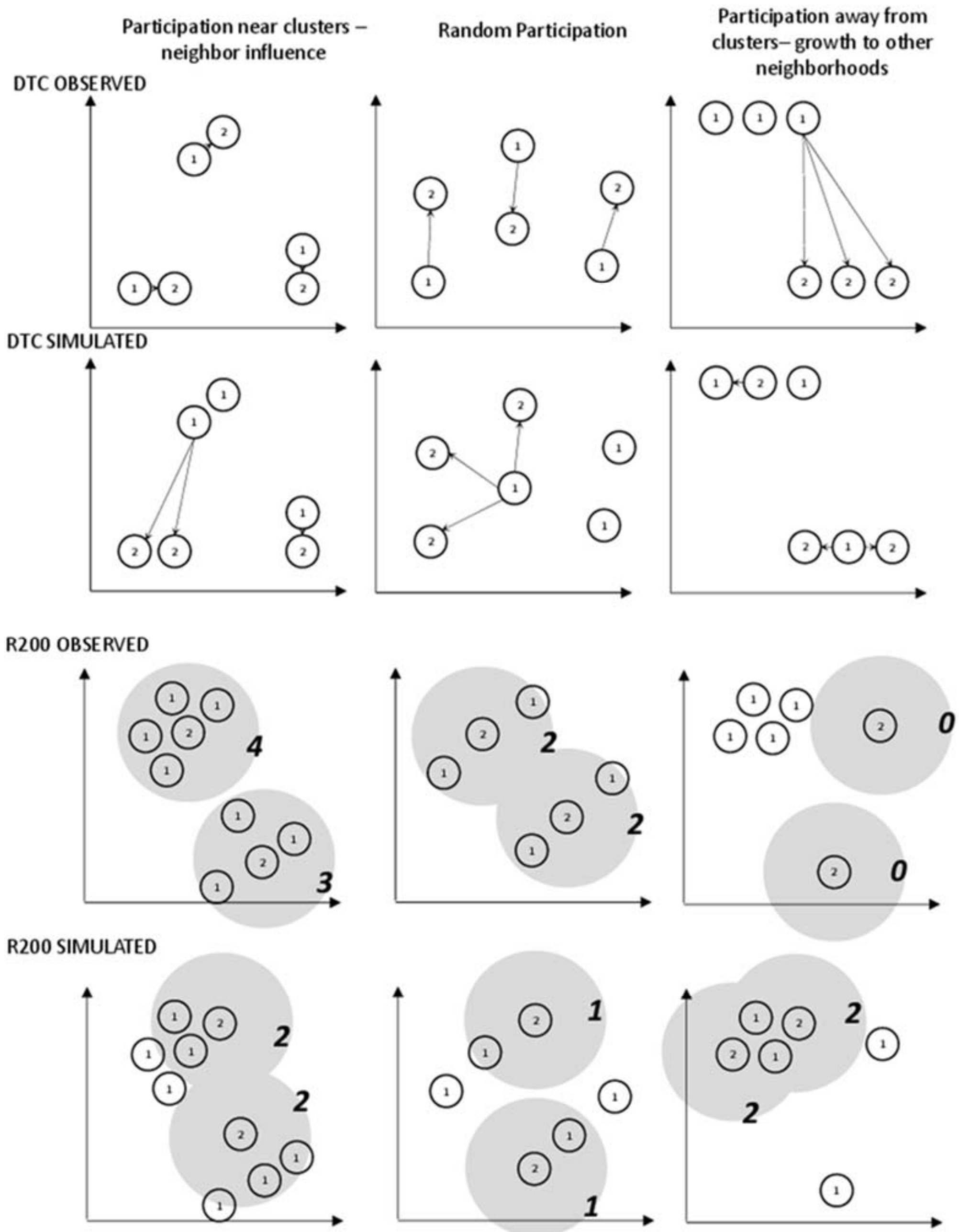

Figure 6.4. Conceptual illustration of observed metrics compared to a time-randomized iteration. Numbered circles represent the year of adoption 1, or 2. The left-most column

demonstrates the case of social influence clustering: the observed DTC metric is expected to be less than the average time-randomized simulation iteration, while the observed R200 metric is expected to be greater than the average time-randomized simulation iteration. The right-most column demonstrates the case of growth to distant neighborhoods: the observed DTC metric is expected to be greater than the average time-randomized simulation iteration, while the observed R200 metric is expected to be less than the average time-randomized simulation iteration. Gray circles represent the area within a given buffer radius of each year 2 participant.

RESULTS

Neighborhood characteristics and overall adoption

The results of the global regression are shown in **Table 6.3.** The full global model includes significant demographic and physical explanatory variables. The full model is able to account for over 50% of the variation in GI participation in census tracts (Adjusted R^2 = 0.53). There is significant improvement in the explanatory power of the model when both sets of variables are included, but the likelihood ratio test (F-test) and Adjusted R^2 values show that more explanatory power is derived from the demographic variables (Adjusted R^2 = 0.35) than the physical variables (Adjusted R^2 = 0.29). The estimated coefficients in the full global model indicate that a 1% increase in the total number of households in a census tract is accompanied by a 2.2% increase in the number of GI installations, controlling for other factors. Higher mean percent imperviousness on residential parcels is associated with higher numbers of participants. However, the significance of a squared term for imperviousness indicates non-linearity. After reaching a turning point at 51.8% mean imperviousness, the effect of impervious area reverses and is associated with decreased participation. Increased numbers of renters is associated with decreased participation, confirming the results of previous empirical research on rain barrel adoption in Chicago (Ando and Freitas, 2011). Higher median incomes are also associated with increased participation, with 1% increase in median income associated with a 0.76% increase in number of participants. Census tracts that are over 80% white on average have 78.9% fewer participants than more diverse neighborhoods. Neighborhoods with higher levels of non-English speakers are also associated with higher numbers of participants, providing evidence corroborating the findings of previous surveys that find that non-White communities expressed greater support of stormwater management installations on private properties (Montalto *et al.*, 2012; Baptiste *et al.*, 2015). The standardized coefficients of the full global model show that the most influential explanatory variable was the total number of households in the census tract, followed by the dummy variable for whether or not the census tract was over 80% white.

A spatial autocorrelation test of the residuals of the full model using inverse weighted distances of the centroids of each census tract and Moran's I revealed evidence of spatial autocorrelation in the residuals of all three global models. The GWR models fit for each census tract capture the heterogeneity in estimated effect of each standardized variable accounting for spatial autocorrelation. As can be seen in **Table 6.3**, not all of the explanatory variables that are estimated as statistically significant at the alpha=0.05 level are estimated to have significant effects in all of the census-tract specific GWR estimates. The only variables that are estimated as statistically significant for all 172 DC census tracts are the log of the total number of households in the tract, the number of renters in the tract, and the dummy variable for whether the tract is > 80% white. The range of estimates of the variables bracket the global full model estimates but capture additional variability of effect distributed over space. Based on the results of the GWR, the most influential variables based on magnitude of the estimated standardized coefficients were the indicator for percent white > 80% (negative effect on adoption) and the average percent of tree canopy for all residential parcels within the tract (positive effect on adoption).

Table 6.3. Global regression and GWR of GI adoption on physical and demographic factors at the census tract scale

	Global Model: Demographic Factors Only						Global Model: Physical Factors Only					
	beta	b[a]	s.e.	p		VIF	beta	b[a]	s.e.	p		VIF
(Intercept)	-18.489	-18.489	3.872	4.E-06	***		7.6	7.6	3.1	0.017	*	
log(Total Number of Households)	2.943	7.051	0.610	3.E-06	***	4.1	-0.48	-1.15	0.34	0.157		1.1
log(Average Parcel Area (sf))							-0.97	-1.84	0.28	8.E-04	***	1.3
Average Parcel Percent Impervious							0.21	0.01	0.05	2.E-05	***	32
Square of Average Parcel Percent Impervious[c]							-0.002	-1.E-06	0.0005	4.E-06	***	33
Average Percent Tree Canopy per Parcel							3.9	30.3	1.40	6.E-03	**	1.9
Number of Renters in Census Tract	-0.003	0.000	0.000	1.E-10	***	4.4						
Percent White >80% (0,1)	-1.036	-2.723	0.400	1.E-02	**	1.5						
log(Median Income)	0.196	0.339	0.300	5.E-01	***	1.9						
Percent non-English speaking >0.3% (0,1)	0.914	2.545	0.359	1.E-02	**	1.1						
Adjusted R^2		0.3543					0.2906					
F stat[b]		3.15E-11					5.02E-14					

	Global Model: Full Model						GWR Results (standardized)			
	beta	b[a]	s.e.	p		VIF	Min	Max	Significant Count	Most Influential Count
(Intercept)	-22.131	-22.131	4.150	3.E-07	***		-46	17	0	0
log(Total Number of Households)	2.245	5.379	0.530	4.E-05	***	4.3	0.37	0.62	172	0
log(Average Parcel Area (sf))	-0.354	-0.669	0.247	2.E-01		1.5	-0.26	-0.06	103	0
Average Parcel Percent Impervious	0.207	0.013	0.043	3.E-06	***	38	-0.04	0.13	111	0
Square of Average Parcel Percent Impervious[c]	-0.002	0.000	0.000	6.E-08	***	37	-0.001	-0.0001	134	0
Average Percent Tree Canopy per Parcel	1.760	13.650	1.451	2.E-01		3.1	0.52	2.4	60	60
Number of Renters in Census Tract	-0.002	0.000	0.000	3.E-07	***	5.1	-0.002	-0.001	172	0
Percent White >80% (0,1)	-1.558	-4.093	0.374	5.E-05	***	1.8	-1.0	-0.7	172	112
log(Median Income)	0.761	1.316	0.289	9.E-03	**	2.4	-0.2	0.4	21	0
Percent non-English speaking >0.3% (0,1)	0.717	1.996	0.309	2.E-02	*	1.1	0.1	0.4	11	0
Adjusted R^2			0.5289							
F stat[b]										

* significant at alpha=0.05, ** significant at alpha = 0.01, *** significant at alpha = 0.001

[a] fully standardized coefficient estimate

[b] F stat compared to full model

[c] the square of the average parcel percent impervious is included to capture a change in direction from positive to negative in the effect of this variable

Social influence

Evidence of significant time-dependent social influence was detected through both the DTC and R200 shuffle tests. Comparison between the simulated probability distribution and the observed DTC suggests that the effect of social influence between neighbors did not become dominant until 2014 (**Figure 6.5a)**. From 2009 to 2010, there is a statistically significant evidence of time-dependency, but 2010 installations were located significantly further from 2009 installation than would be expected from a distribution of time-independent simulations (>99.9% percentile). After the first year of implementation, the observed DTC relative to the simulated probability distribution appears to reflect the right-most situation in **Figure 6.4,** where growth to distant areas outweighs proximate social influence of neighbors. Over time however, the influence of growth to distant areas is gradually outweighed by the influence of proximate neighbors. By 2014, the observed DTC is significantly lower than what would be expected from a distribution of time-independent simulations (<0.1% percentile).

The results from the R200 metric shuffle test support the finding that participation growth first occurred in distant areas after the first year (**Figure 6.5b**). The observed mean number of previous participants within a 200-m radius of each 2010 participant was significantly lower than expected from a distribution of time-independent simulations (<0.1% percentile). This situation again reflects the right-most situation shown in **Figure 6.4.** After three years however, this relationship reversed itself, and the observed mean number of previous participants within the 200-m radius of each 2012 participant (4.65) was significantly higher than expected from a distribution of time-independent simulations (mean = 3.89 within 200m radius; percentile>99.9%). This is more reflective of the left-most situation shown in **Figure 6.4**.

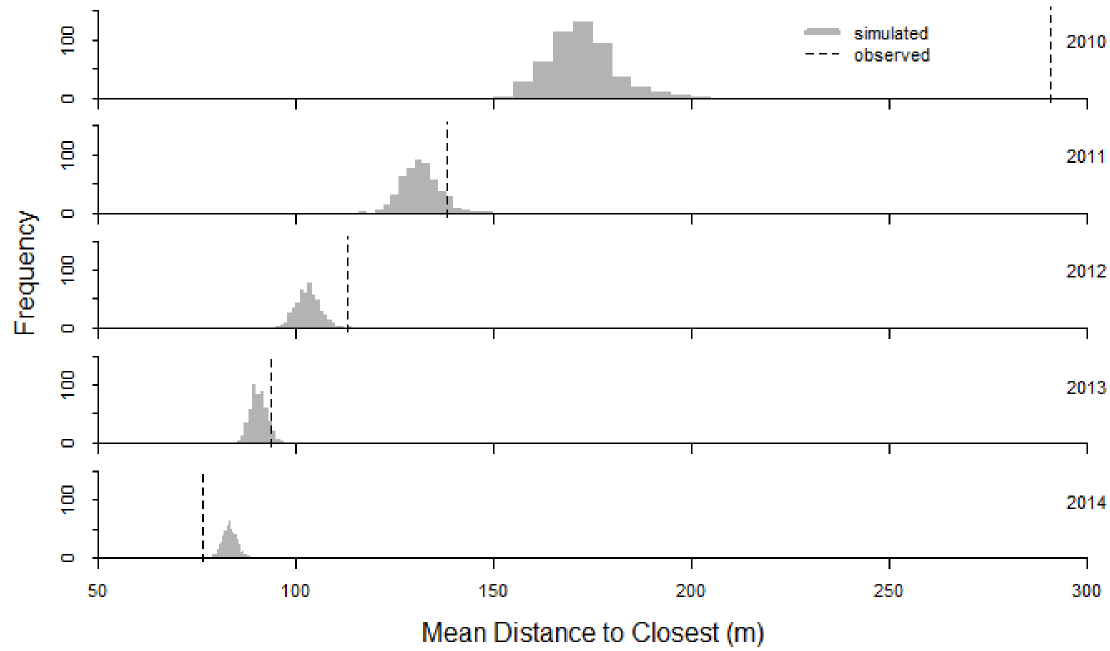

Figure 6.5a DTC comparison between simulated probability distribution and observed DTC (dashed line). 2010 percentile > 99.9; 2011 percentile =91.6%; 2012 percentile =99.6%; 2013 percentile < 91.8%; 2014 percentile < 0.1%

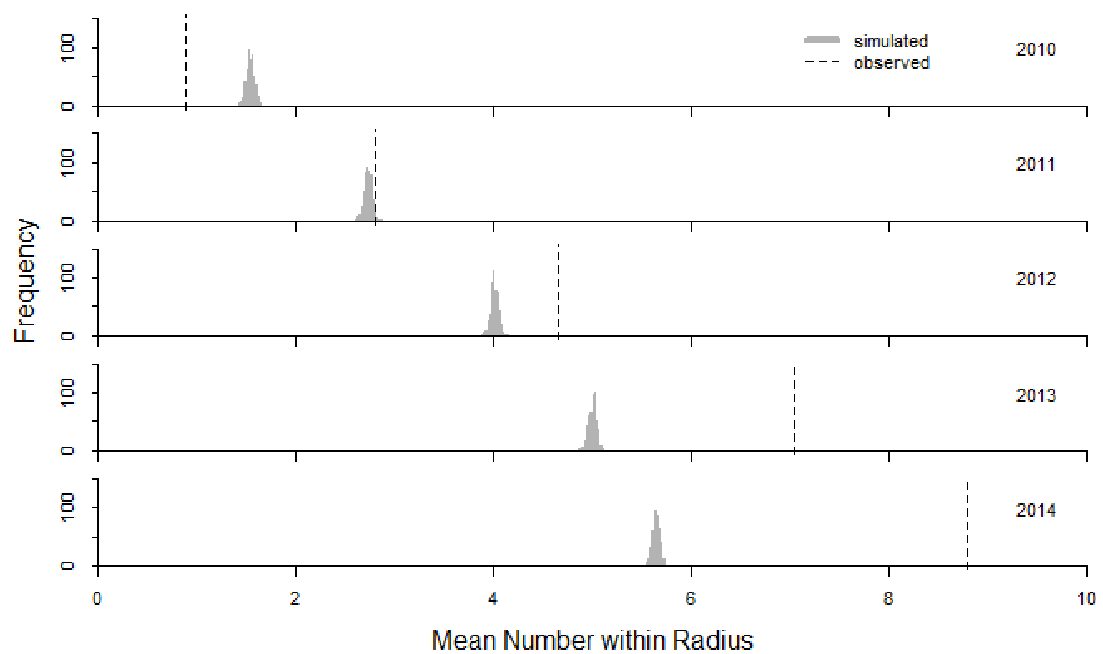

Figure 6.5b Comparison between simulated probability distribution and observed R200 (dashed line). 2010 percentile <0.1%; 2011 percentile = 93.6%; 2012 percentile > 99.9%; 2013 percentile > 99.9%; 2014 percentile >99.9%

DISCUSSION

The regression results from this study confirm the survey results from other studies. Addressing spatial autocorrelation of residuals fit from a 'global' ordinary least squares regression model revealed how the magnitude of estimated effects of variables vary across the city. Further study of the variation of these effects may help identify reasons why some variables are more/less influential in certain neighborhoods. What is clear from the regression analysis however is that neighborhood demographic variables are able to explain more of the variation in participation than physical characteristics. Since the dependent variable was the log of the number of installations of *any* type of GI (rain barrels, rain gardens, bayscaping, shade trees or permeable pavement), residents willing to participate in the program are more likely to be able to choose an intervention compatible with the physical constraints of their properties. This would decrease the influence of physical factors compared to social factors.

The results of the GWR estimates of standardized explanatory variables also revealed that adoption of GI may be driven for different reasons in different areas of the district. While the total number of households, the number of renters and a high proportion of white residents were factors that were significant in explaining the number of GI adoptions in every census tract, other factors, such as level of imperviousness, average parcel area, tree canopy cover, and median income were only statistically significant in explaining GI uptake in a subset of census tracts. Among census tracts were mean tree canopy cover was significant (62), tree canopy cover was the most influential variable explaining GI adoption in 60 of them.

Combining the findings of the regression analysis of overall participation with the findings of the shuffle tests allows for additional interpretation beyond similar studies that have sought to explain GI adoption using neighborhood characteristics. Instead of neighborhood characteristics reflecting the environmental attitudes, preferences of the participants, these characteristics could be more reflective of information flows and strength of social influence.

The findings of the shuffle tests demonstrated evidence that residents tended to participate close to previous participants even after controlling for increased density of the installations over time and for unobserved individual-level attributes that would cause people who live near each other to independently participate in the program. However, this pattern emerged only after a certain period of program growth to more distant areas. For the DTC metric, statistically significant proximate social influence was not evident until the fifth simulation year, compared to in the third simulation year for the R200 metric. An explanation for the difference in timing of this trend is the sensitivity of the DTC metric to distant outliers. Results of subsequent tests revealed, as expected, that as the buffer distance of the counts-within-radius metric is decreased (for example, R100), more years were necessary to detect statistically significant evidence of proximate social influence. As the radius was increased (for example to R300), evidence was apparent in the second year.

The patterns of social influence in a subsidized GI program detected in this research suggest that residential GI adoption can be viewed within stages. In the first stage (first 1-2 years of the program), early adopters contribute to the growth of the program throughout the city. In the second stage (years 2-4), the effect of locations of previous adopters begins to determine locations of subsequent adopters, outweighing growth to distant areas. In the third stage (years 3-5), adoptions by residents proximate to previous adopters becomes the dominant growth dynamic for the program.

Limitations

The main limitation of the shuffle test is the assumption that individuals' location-based attributes are time-invariant. In reality, it is plausible that the locations of and demographics of decision makers are changing, and that this may be what is driving spatial-temporal dependence of GI adoptions. Systemic neighborhood demographic change over time is one example of a time-dependent change that might simultaneously drive GI adoption patterns. In the shuffle test, this pattern might appear like a neighbor's adoption 'influenced' a subsequent neighbor's adoption, when in fact one or both may have been driven by external trends. A time-dependent confounding factor includes real estate agents promoting the RiverSmart Homes program to their clients as a way to upgrade the property's landscaping. In this study these influences are assumed to be minimal compared to the influence between proximate neighbors spreading information and "displaying" their installations. However, the magnitude of such influences also likely vary across the city. Unfortunately, this study did not include sufficient observations to compare the results of shuffle tests from different census tracts. Compared to other models which seek to capture time dependency of information spread, including other resampling techniques (La Fond and Neville, 2010), and panel-based regression (Geroski, 2000), this study does not control for individual attributes, and therefore is unable to compare the relative impacts of social influence versus personal preferences on participation in voluntary GI programs.

What is unclear from this research therefore is whether normative-based peer pressure has resulted in changes in environmental attitude, or, if social influence is occurring through neighbors merely spreading information about the existence of the GI subsidy program. The choice of years as the time increment for the shuffle test is based on the assumption that other types of place-based program promotion would be expected to produce quick “bursts” of proximate participation as opposed to months-long or years long spatial-temporal dependence. However, I acknowledge that this logic is an imperfect proxy for conducting in-depth surveys for both how people learned of the program, and the spatial locations of their information sources. Follow-up research could collect information about participant locations and knowledge about previous participants to address this gap. Previous research has shown a tenuous relationship between knowledge of environmental function of GI installations and motivation to install GI (Roy *et al.*, 2008; Londoño Cadavid and Ando, 2013; Brown *et al.*, 2016). Perhaps such a shift in the role of social influence would constitute a future “fourth phase” of voluntary residential adoption of GI. This fourth phase would then begin to appear like the eco-normative feedback mechanisms that have been shown to be influential for energy and water consumption “nudge” type initiatives (Allcott, 2011; Jain *et al.*, 2013; Schultz *et al.*, 2016).

CONCLUSION

This research provides evidence that social influence between neighbors is a significant pathway for residents to find out about the River Smart Homes programs. Residential GI adoption shows evidence of positive social influence and that this influence results in clustered growth that outweighs growth to new areas after 2-3 years of program implementation. Showing that GI adoption is similarly responsive to peer influence for other environmental behaviors, such as water and energy conservation and solar panel installations has implications for planners. The visibility of GI installation compared to other environmental behaviors makes it ideal to spread through space-based social networks as residents interact with each other and their local neighborhood environments. This suggests that planners should leverage the visibility and aesthetic of GI in high traffic areas to disseminate information about how to participate in voluntary programs and make positive impacts on the environment and enlist influential community members as “neighborhood ambassadors” for GI programs.

The findings of this study also demonstrate the importance of distinguishing between personal willingness to adopt GI, physical feasibility and social processes of information dissemination, as empirical correlation between low participation and certain social characteristics may be more attributed to limitations of program awareness than conscious preferences of residents. In addition to relevance for voluntary GI adoption programs, this finding is also useful for programs that rely on economic incentives as motivation for private adoption of GI. Social influence through neighborhood “ambassadors” and highly visible installations may increase initial awareness and confidence in this ‘new technology’ to spur participation in combination with economic or normative approaches to encouraging residential participation.

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CHAPTER 7: CONCLUSIONS AND IMPLICATIONS

SUMMARY OF CONCLUSIONS

The aspect of Green Infrastructure planning that most differs from conventional infrastructure planning is the distributed nature of its functional processes and implementation. In this dissertation, I have improved understanding of three major previously unanswered questions about its function. First, in Chapter 3, I showed that the loss of incremental storage within watersheds is just as associated with low density suburban development as it is with highly impervious urban areas. This finding indicates that planners' previous focus on impervious surface-based development metrics for natural hydrology protection is incomplete. Second, in Chapters 4 and 5, I tested the sensitivity of a representative residential urban sewershed to various changes in spatial configurations of imperviousness and GI networks. I found that coupled surface-subsurface modeling is important in capturing inter-event capacity recovery in urban catchments relying on infiltration and evapotranspiration to manage stormwater runoff. However, at this scale, different spatial configurations that might occur due to distributed residential GI adoption patterns are not likely to have a detectable effect on hydrological effectiveness. Lastly, in Chapter 6, I showed how spatial patterns of GI adoption shift from growth to new neighborhoods to clustered around previous participants over time.

IMPLICATIONS FOR PRACTICE

Following the flooding of Ellicott City, MD's historic downtown in 2016, Howard County was correct to re-examine the effect of continued development on downstream changes to hydrologic response. Even if new developments are "treated" with GI stormwater management facilities or designed according to Low Impact Development principles, such practices are unlikely to be able to mitigate all changes to the hydrologic cycle that come alongside development.

Instead, cities and regions should prioritize natural land conservation as part of their toolbox for preserving the natural hydrological cycle. In addition to the focus on the most visible aspect of the effect of urbanization on the hydrological cycle—runoff generated from impervious surfaces—the effects of natural soil and vegetation conservation may have an even larger effect than removing imperviousness. This is because the process of urbanization is accompanied by drastic changes to the hydraulic conductivity of soils, soil compaction, and the density of vegetation, in addition to the increase of imperviousness. Incremental hydraulic connectivity in natural areas can be maintained if they are left free of drainage infrastructure. Beyond preserved hydrological function, undeveloped lands provide opportunities for recreation and can contribute to higher property values and overall improvements in quality of life. Resisting development in conservation areas will require the economic justification of natural infrastructure and ecosystem services to society (eg: Schäffler and Swilling, 2013). While financially quantifying the value of conservation is beyond the scope of this dissertation, the findings of this research might be incorporated into such an evaluation.

This empirical finding that development, and not type of development is more influential to the loss of incremental storage in urbanized watersheds contradicts the results of models that are based on simple land use conversion and land cover models (eg: Wu *et al.*, 2015), but affirms other studies that incorporate more complex hydrological processes that could influence variable source area, or non-constant contributing areas in response in catchments (eg: Bhaskar *et al.*, 2015). This suggests that policy that uses urban growth scenarios to evaluate effects on hydrologic response may be overestimating the effectiveness of engineered GI on the regional hydrological regime, and underestimating the value of natural conserved land (evapotranspiration from forested land, for example). It also suggests that subdivision and land development regulations that require the retention of trees above a certain pole size and the planting of vegetation are well justified. An example of a more comprehensive zoning regulation is DC's "Green Area Ratio," which in addition to the subdivision and land development ordinances tools of setback requirements and lot bulk coverage limitations, also includes a weighting scheme for additional environmental benefits associated with landscape features (https://doee.dc.gov/node/619592). While setback requirements and bulk lot coverage limitations focus on limiting site imperviousness, metrics like the Green Area Ratio will be able to take into better account ecosystem services associated with mature trees, native vegetation, and leaf area ratios. At the regional scale, such factors may play a large role in restoring incremental storage exceedance patterns that we associate with undisturbed watersheds. Unfortunately, but perhaps not surprisingly, even after the deadly Ellicott City flood, the proposed development moratorium was not passed because of its political unpopularity. This illustrates the particular challenge of the role of the city planner as an actor within the urban growth machine, and the need for additional proof that natural land preservation does serve critical flood regulation function.

The pursuit of "near natural" water budgets reflects the desire to replicate pre-development ecological conditions to reduce the effects of urbanization on the natural environment (Feng *et al.*, 2016). This normative design goal is promoted by EPA standards and technical handbooks, as well as rating systems such as the USGBC's LEED system http://www.usgbc.org/) and the Envision™ sustainable infrastructure system (http://sustainableinfrastructure.org/envision/), and is steadily becoming more of an industry standard as more engineering and construction firms gain capacity in GI design. This increase in multi-objective infrastructure planning is a good thing. However, we must also keep in mind the limitations of model-based evidence of reaching “near natural” post-development water budget goals, since most hydrologic models are not developed to capture the changes in evapotranspiration and soil hydraulic conductivity that accompany urbanization. This is especially true for greenfield development, where the consequences of engineered GI not truly enabling the site to reach “near natural” hydrological conditions will be more severe for the surrounding aquatic habitat than for a brownfield redevelopment site that in either case, is served by municipal drainage infrastructure. In fact, for an appropriately-sized CSS, runoff is intercepted by the drainage system, treated at the wastewater treatment plant, and released as treated effluent. The collection and treatment processes would smooth out the peaks of storm events and would remove pollutants that some engineered GI might not be able to mitigate.

Related to this, is the second implication for practice: continued GI data collection and monitoring is necessary. There is still limited empirical research showing catchment-scale effects of engineered GI on hydrological regime and water quality. Empirical, statistical analysis of urbanized areas with and without GI in the Maryland-Washington DC region, where GI has already been adopted at rates high enough to begin to detect statistical differences, did show evidence of less flashy hydrology (Pennino *et al.*, 2016). This region has collected large amounts of GI data (including contributing areas and locations of GI installations) as well as flow and water quality data. As more urban catchments implement GI across the US, we can expect more urbanized catchments to cross thresholds of catchment-scale hydrological effectiveness. In order to truly assess variation in effectiveness associated with engineered-GI at the catchment scale, data on GI implementation should be publically available, and policy should include the collection of relevant long-term monitoring data. In this dissertation, I conducted a statistical study of urban variable source area using USGS stream gauge flow data only, but important long-term water quality parameters, including nitrate (NO_3^-), total nitrogen (TN), phosphate (PO_4^{3-}), and total phosphorous (TP) available in the Baltimore region enabled closer examination of the effectiveness of GI on water quality in this geographic area. These data have been collected through various programs, including the EPA and USGS, but also regionally specific initiatives, such as the Baltimore Ecosystem Study Long-term Ecological Research (http://www.beslter.org/data) site and the Clean Water Baltimore (http://cleanwaterbaltimore.businesscatalyst.com) Sampling Program (Pennino *et al.*, 2016). The use of GI to both improve infrastructure function and to improve environmental conditions fits into the adaptive management regulatory framework. This regulatory framework requires policy innovation and urban experimentation and theoretically should afford communities the agility to adapt to changing conditions of urbanization and climate. This adaptive management is only possible with continuous data collection, modelling and reassessment when interim goals are not met, or when conditions are not stationary.

The third implication for practice from this dissertation is that the distributed nature of GI has the potential to be more of an asset than a challenge within cities. GI is a distributed infrastructure that can be deployed simply as a change to a property owner's landscaping practices. On the one hand, this could be viewed as a challenge, because compared to traditional, centralized infrastructure planning, engineers have little control over the landscaping and land management practices of hundreds of thousands of property owners. On the other hand, this dissertation showed that precise spatial configurations are not likely to result in detectable differences in hydrologic response on the sewershed scale, and that participation in voluntary GI programs spreads through spatially-dependent social networks over time. Within any given sewershed, there is no reason to spend resources in property-specific targeting or land acquisition strategies to "optimize" GI placement to avoid decreased effectiveness of GI networks. Note that this does not imply that implementation of GI at the city scale need not consider spatial location of GI. However, such a conclusion is likely to be dependent on the capacity and needs of the existing infrastructure, rather than on the natural processes of groundwater dynamics and evapotranspiration that were hypothesized to potentially impact capacity recovery differentially across space.

Without the burden of spatial optimization from a hydrological perspective, GI planners and policymakers could shift their attention to other reasons for spatially targeting outreach to potential participants in distributed GI programs. For example, the spatial distribution of green space within cities is partially driven by overall market-driven redevelopment rates and investment, and is associated with larger properties and higher income levels (Heckert and Rosan, 2015; Lin *et al.*, 2015). Targeted investment of GI implementation for traditionally disadvantaged residents is one way to encourage urban equity through community development and increased environmental amenity and beautification (Spirn, 2005; Baptiste *et al.*, 2015).

As with other new technologies, it will take time for GI to catch on among residents, but the findings for this dissertation are encouraging because there is evidence of socially-dependent dissemination. The hard work of outreach and publicity about voluntary GI programs after five years of implementation, has shifted from the planning agency, to past participants. In fact, in 2015, according to one planner involved in Washington DC’s voluntary residential GI program, the limiting factor for increased implementation is now availability of funds where previously the limiting factor was residents’ willingness to participate in the program.

FURTHER RESEARCH

In this dissertation, I explored a range of scales and dimensions of the socio-ecological systems of green infrastructure and stormwater runoff. But there are still many outstanding questions about how scale and type of GI will actually result in measurable improvements in the aquatic habitat. GI that is planned for and implemented as part of the NPDES permit requirements for an MS4 or CSS should be viewed as a way to reach compliance as a point source. While this is one step towards meeting the goals of the Clean Water Act, it does not necessarily translate to improved water quality in impaired water bodies. This question will rely on how infrastructure outfalls, as a large-area point source, compare to other sources (some of which may be even more dispersed, such as agriculture or atmospheric deposition), in determining water quality. Situating both the current and potential capacity for urban areas to improve water quality within the larger context of other sources of water quality impairment will help policy makers and planners budget funding for water quality improvement plans at various scales.

This dissertation was mostly concerned with hydrological regime changes, rather than on water quality parameters. Urbanization is accompanied by decreased storage and flashier runoff response, as well as increased pollutant loadings. Pollutant loads are also dependent on land use type, and GI will be able to reduce certain types of pollutants more efficiently than others. For example, in Chapter 2, I showed how low density developed open space exhibited loss of variable source area-type response in a similar way to high-density urban cores. However, those different land use types would also be expected to exhibit different pollutant loading profiles. Additional research could investigate the interaction between variable source area-type response and pollutant profiles.

The research on sensitivity of hydrologic response at the sewershed scale to the spatial configuration of imperviousness and GI networks could be broadened to examine the conditions under which a “high capacitance” catchment begins to transition to a catchment that exhibits evidence of having “low capacitance.” Over the past three decades, there has been much interest in identifying thresholds of hydrologic change. The most well-known example, Schueler’s 10 percent rule of thumb, which stated that watersheds that were covered in over 10 percent impervious surface area had detectable signs of impairment, is still commonly referred to today (Schueler, 1994; Schueler *et al.*, 2009).

Unfortunately, going the other way, from a “more developed” state to a “less developed” state through GI retrofits will require larger changes to the developed landscape. This dissertation showed that differences in the rainfall-runoff ratio were only detectable after between 36 percent to 100 percent differences in (non-GI treated) impervious area on the site compared to the levels of variation present in monitored pipe flow data. Differences in the rainfall-runoff ratio between spatial configurations of GI networks of equal treated area were observable only when the total area treated with GI exceeded 14 percent. In another study, no observable differences were observed until 7 percent of the watershed area was retrofit with GI (Miles, 2014). Greater definition of when such thresholds in behavior and behavioral metrics, and under what conditions they exist would be useful to communities that would like to know at what point GI networks could reach an upper limit of effectiveness.

This highlights the intuitive yet often overlooked distinction that cities that wish to restore environmental or infrastructure function are facing a fundamentally different problem than developing cities that wish to maintain the ecological function of undeveloped land. This means that it is appropriate to adopt subdivision and land development ordinances for greenfield development that are different from ordinances for existing site redevelopment. Ten percent disturbance of greenfield land for development is not the same as treating 10 percent of impervious surface in an urban context. According to this study, the latter would not be expected to result in any detectable difference in monitored pipe flow runoff volumes.

Lastly, more empirical research is needed to determine the exact social processes through which voluntary GI adoption is spreading. In this dissertation I showed evidence of social processes of GI program growth. Programs such as the RiverSmart Homes program are entering a stage of maturity that allows for reflection on best practices for city-wide implementation. Understanding the time-dependent responsiveness of how residents' landscape management practices will allow cities to plan for how long it may take distributed property owners adapt to changing infrastructure, climate, and development conditions for the benefit of the overall urban environment.

For example, while a particular city's storm or sewer infrastructure may currently necessitate mitigation of runoff from the first inch of rainfall, increased intensity of precipitation patterns may require more source control measures for that same system to be functional in the future. Knowing how quickly property owners will voluntarily adapt their landscaping practices given these nonstationary planning conditions will be very useful. In contrast to redevelopment rates that would trigger mandatory regulatory ordinances, growth rates of voluntary participation programs would capture an important mechanism for adaptive management, as well as a means for the city to invest in communities where real estate development may not be a primary driver of property upgrading.

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